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The Effect of the Texas 10% Law on Applications, Admissions, Enrollment and Student Outcomes – Regression Discontinuity Evidence[♦]

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Abstract

We examine the effects of the Texas 10% rule. The rule states that students who graduated among the top 10% of their high-school class are guaranteed admission to public universities in Texas. Theoretically, this law could affect the application choices of students, the admission committee decisions for those who applied, and the enrollment decisions for those who are admitted. We exploit the discontinuity in the relationship between class rank and the decisions of students and admissions committee to identify the effects of the policy. The law has been both promoted as a way to increase diversity without explicitly using racial criterion, as well as derided for creating "mismatches" by admitting students who are unprepared. We do not find clear support for either claim. We do find that the guaranteed admission to public universities reduces applications to competing private universities.

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1. Introduction

The Texas 10% rule states that students who graduated among the top 10% of their high-school class are guaranteed admission to public universities in Texas. In part, this law was created to reduce the drop in minority enrollments seen following the judicial ban on affirmative action practices. While the law is not race-based per se, it uses the substantial segregation across high schools in Texas to attempt to increase minority enrollment. Critics of the law suggest that it has led to the enrollment of less qualified applicants — top 10% students from low-quality high schools — creating a "mismatch" and thus both reducing rates of college completion and crowding out other applicants who would have been admitted without the law.

Several empirical evaluations of the law have been conducted. The empirical strategies have typically been a pre/post analysis, and the general findings suggest that minority enrollment was increased due to the law but not to the levels before the affirmative action ban.[1] Few studies have supported claims of "mismatch".[2] No current analysis has examined the potential behavioral reactions by both students and the university admission committees.

We examine the effects of the law along multiple decision margins: Students' application behavior, admission decisions by the university, enrollment choice conditional on admission; as well as the resulting college achievement. Intuitively, our identification strategy amounts to comparing students just above and just below the 10% cutoff. We assume that other student characteristics and incentives are continuous at this cutoff. We examine if we are able to detect a jump in probabilities of application, admission, or enrollment at the 10% cutoff. We also look for discontinuities in characteristics of students conditional on these decisions, as well as student performance.

While other researchers have used the Top 10% Law in a regression discontinuity (RD) framework, they have typically focused on the effects of attending a more selective college on

[1] Bucks (2004), Harris and Tienda (2010), Koffman and Tienda (2008), Long and Tienda (2008)
[2] Cortes (2008), Furstenberg, (2009)

later outcomes, such as college success (Cortes, 2009 and Furstenberg, 2010) and post-college wages. Thus, these papers focus on the "treatment" of attending selective college versus the "control group" who attended a less selective college due to the Top 10% Law. In contrast, we compare two students who both apply to, are admitted to, or attend a specific college, such as Texas A&M. In our case, the "treatment" is whether the student is guaranteed admission due to her high school rank.

We focus on the two flagship universities, the University of Texas at Austin (UT) and Texas A&M University at College Station (A&M). We do not find evidence that the admissions guarantee increases the application probability of marginal top 10% students to the two flagship universities. We find some limited evidence that the Top 10% Law affects the characteristics of applicants. At A&M, SAT scores of applicants slightly above the threshold are 1/10th of a standard deviation lower than those of applicants just below the top 10%. For UT, we find that applicants slightly above the threshold are 2 percentage points less likely to be from feeder high schools (high-schools that traditionally send many students to the university) than applicants just outside the top decile. In other words, the admissions guarantee induces students from non-feeder high-schools to apply. At the same time, we detect a drop in applications to private universities (Rice and SMU) for students just inside the top 10% of the high-school class, suggesting that guaranteed admission at UT or A&M makes applications to the private schools less valuable.

The law alters admissions decisions – mainly at the University of Texas at Austin. While students in the top 10% are always admitted, students just outside the top 10% have an 80% admissions chance at UT and a 95% admissions chance at Texas A&M. For A&M and UT, admitted students just inside the top high-school decile are less likely to be male – the 10% rule leads to a higher admission rates for female student. For UT, we find some evidence that the Top 10% Law promotes ethnic diversity and that students from a feeder school are less likely to be admitted based on the law. We find no differences in the SAT test score performance for students admitted under the law versus those admitted by the committee.

Conditional on admission, students in the top high-school decile are more likely to enroll at A&M than students just outside the top decile. At UT the result is reversed – conditional on admission students with initially guaranteed admission are less likely to enroll than similar students whose admission was not guaranteed. The 10% rule does not lead to a statistically significant increase in minority enrollment – even though our point estimates suggest some effect.

At Texas A&M there is no evidence that students from the top high-school decile perform worse than similar students just outside the top decile. At UT we find mixed evidence. The top 10% students tend to choose easier majors and are slightly less likely to stay enrolled for more than 3 years. We find no evidence of an effect on GPA.

2. Effects of the 10% Rule

We investigate a number of behavioral consequences of the 10% rule. To identify theses effects we exploit the fact that the 10% rule creates a known discontinuity in admissions probability at the 90^{th} percentile of a high school class. Our RD research design is motivated by the notion that students who are ranked in the 10^{th} percentile in their graduating class provide a good counterfactual to students ranked in the 11^{th} percentile. In order for this assumption to be valid, student characteristics should be continuous through the threshold. We consider four sequential stages: First, students decide whether to apply to a university. Second, the university's admissions committee decides whether to admit a student. Third, admitted students decide whether to enroll. Fourth, enrolled students obtain an outcome in the form of grades or graduation.

Application

Students in the top 10% of their high-school class know that their admission to a state school in Texas is guaranteed. This increases the benefit of an application to such a school. At the same time the guaranteed admission reduces the need to insure against non-admission. This reduces the

benefit to applying to other schools – these other schools could be less preferred state schools or private universities. A student with high test-scores has a high probability of admission – an admissions guarantee affects them less than students with low test-scores. Hence the behavioral differences between students just inside and outside the top decile are expected to decrease in test-scores. A similar story can be told for other characteristics that are correlated with admissions probability.

Admission

The 10% Rule mandates that students in the top 10% of their high-school have to be admitted to state schools. How important is this effect? – would they have been admitted anyway? We address this question by comparing the admissions probabilities of students in the 10^{th} and 11^{th} high school percentiles. Due to the effects of the rule on the composition of applicants, the actual difference in admissions probabilities may be understated. For students outside the top high-school decile, the admission committee may take students characteristics into account when determining whom to admit. We compare the characteristics of admitted students just inside the top decile to students just outside the top decile. The composition of admitted students depends on the effect on application and admission conditional on application.

Enrollment

We examine the decision made by students to accept admission. The effect is ambiguous – the admissions guarantee might induce students to only apply to their preferred school and enroll at that school. Another possibility is that the admissions guarantee makes a school interesting to insure against non-admission at a preferred school. This could lead to lower rates of enrollment conditional on acceptance. The overall effect of the 10% rule on the composition of the student body depends on the combined effects of the three stages: application, admission, and enrollment.

Outcomes

By comparing students just above and below the automatic admission threshold, it is possible to examine the "mismatch" hypothesis. If students just inside the top 10% perform worse than students just outside the top 10%, the policy leads to mismatch.

3. Data

We use administrative data from several public and private universities in Texas. We focus on the flagship institutions: the University of Texas-Austin and Texas A&M University. These data were collected under the auspices of the Texas Higher Education Opportunity Project.[3] For most schools, we have data for the universe of all applicants for the decade beginning with the 1992 school year. Thus, we can examine cohorts during several admission regimes, including Affirmative Action (1992-1997), no Affirmation Action and no Top 10% Law (1998), and the Top 10% Law (1999-2002).

Two types of administrative records are available for each university. A baseline file includes all students who applied in a given year, their admission decision, and conditional on acceptance, their enrollment decision. The baseline file also contains a large set of student characteristics, including high school rank, SAT/ACT score, race, gender, identifiers of high school of origin, and other measures. For matriculants, a term file records various measures of academic progress, notably persistence, GPA, choice of major, and graduation status for each semester enrolled.

Descriptive statistics for the analysis samples (near the high school rank threshold) for TAMU and UT-Austin are presented in Table 1. Appendix Table 1 shows results for the full sample. Admission rates around the 10% cutoff are 88% at UT and 93% at TAMU; the appendix

[3] THEOP is a longitudinal study of college-going in Texas designed to understand the consequences of changing admissions regimes after 1996. The description of this project is available at www.THEOP.Princeton.edu.

table shows the rates for the full sample of applicants is 73% for each school. Unconditional enrollment rates are approximately 55-60% of all applicants. Minority (African American/Hispanic) students make up 22% of applicants at UT and 15% at TAMU. Students from "feeder" high schools (those with histories of sending students to the university) comprise 19% of UT applicants and 15% of TAMU applicants. The average SAT score for UT applicants was 1181 and 1144 at TAMU. The table also presents these summary statistics conditional on admission and enrollment decisions. Finally, we descriptive statistics are shown for several college success measures, including GPA, persistence, graduation rates, and choice of major.

4. Empirical Specifications and Results

Our empirical strategy is to compare students "close" to a 10-percentile high school class rank for a range of outcomes, including application decisions by the students, admission decisions by the universities, enrollment decisions by the admitted students, and student college outcomes of enrollees. We separate our empirical analysis into four sequential steps – application, admission, enrollment, and university performance.

Responses to the Law 1: Student Application Patterns

We first examine application decisions of students. We estimate whether the admissions guaranteed increases or decreases the probability that a student applies to UT, A&M, or a private University in Texas.

We define $1/10^{th}$ of a percentile bins for the high-school rank and count the number of applicants in each bin. We assume that the number of high-school graduates in each bin is continuous at the 90^{th} percentile in the high school class rank distribution, where the top 10% law is implemented (i.e., the number of graduates between the 89.9^{th} and 90^{th} percentile is equal to

the number of graduates between the 90th and 90.1th percentile).[4] Our second assumption is that without the 10% rule the probability of applying to a University is continuous at the 90th percentile. Consequently, without the 10% rule the number of applicants would be continuous at 90th percentile; any discontinuity can be interpreted as the result of the 10% rule.

Figure 1 displays the raw data as well as a lowess smoother of the number of applicants by the 1/10th percentile bins below and above the 90th percentile. The figure shows the results for UT-Austin on top and for Texas A&M on the bottom. For either school, it is not possible to visually detect evidence of a jump up or down as the 90th percentile threshold is passed.

To formally investigate whether the number of applicants jumps at the 90th percentile we use a locale linear regression to detect a jump at the 90th high-school percentile. We estimate:

$$\left(\#applicants\middle|r_i\right) = g\left(r_i - c\right) + \delta D_i + \beta_1 D_i g\left(r_i - c\right) + u\,, \qquad (1)$$

Where *r* indicates high school class rank, $g(.)$ is a continuous function, the dummy variable D captures changes at the threshold ($D_i = 1$ if $r_i \geq c$, and $D_i = 0$ if $r_i < c$), and the associated coefficient δ captures jumps at the threshold. The results for UT and A&M are displayed in columns (1) and (4) of Table 2. There is no evidence for a jump at the 90th percentile.

Guaranteed admission to the flagship schools could lower the likelihood of applying to other universities. While we do not have data on the complete application portfolios of students, we do have data on other Texas universities. In particular, we examine two private universities that compete with the flagship universities for high performing students: Rice University and Southern Methodist University (SMU). We pool these schools and focus on overlapping years of available applications data in order to increase sample size: 2000-2004. Figure 2 displays the number of applicants in the 1/10th percentile bins below and above the 90th percentile. Estimating (1) for the private universities provides evidence of reductions for students in the top decile in

[4] This assumption technically holds by definition. However, since the public universities allowed students to use either their class rank during the fall or spring semester of their senior year, there could be some shifts in the distribution of the measured high school class rank variable.

their graduating class. Column (7) of Table 2 displays a estimate for δ. Individuals who are guaranteed admission to a flagship school are less likely to apply to SMU or Rice.

Next, we examine whether the composition of applicants changes around the cutoff. We estimate the following regression model:

$$X_i = g(r_i - c) + \delta D_i + \beta_1 D_i g(r_i - c) + u_i \qquad (2)$$

where X_i captures a characteristic of the applicant pool. The coefficient of interest is δ, which measures whether the composition of applicants changes discontinuously at the threshold. We focus on student race/ethnicity, gender, SAT scores, and high school of origin. The results are shown in Table 3. We do not find evidence that the admissions guarantee has different effects on the application decisions of minority or non-minority students. For UT, we find evidence that students who are slightly above the threshold are 2 percentage points less likely to be from feeder high schools. For A&M the point estimate for feeder schools is similar but the result is not statistically significant. We find no connection between admissions guarantee and application behavior at UT. For A&M, however, we find evidence that SAT scores of students slightly above the threshold are about 1/10 of a standard deviation lower than those of students right outside the threshold. In other words, students with lower SAT scores are encouraged to apply due to the admissions guarantee. [5]

Responses to the Law 2: Admission

The 10% law guarantees admission for students in the top high-school decile. We examine if these students would have been admitted without the rule. For all applicants to a school we estimate:

$$Admit_i = g(r_i - c) + \delta D_i + \beta_1 D_i g(r_i - c) + u_i ,$$

[5] We show in Table 2A in the appendix that these results are similar with alternative bandwidths.

where $Admit_i$ equals one if the student is admitted and zero if she is not admitted. The results are displayed in columns (1) and (6) of Table 4. We see that individuals slightly above the threshold experienced an increase in the probability of admission of 17 percentage points at UT and 4.5 percentage points at A&M. The reason for the smaller change for A&M applicants is that students with class ranks in the second decile are admitted at a rate of 90% or more so that moving to a 100% admission probability is not a large change.

The total effect of the 10% rule on admissions is a combination of the effects on application and admission. We examine whether the total number of admitted students in each $1/10^{th}$ percentile bin jumps at the 90^{th} percentile. Columns (2) and (5) in Table 2 reveal a positive effect for UT – the effect is smaller for A&M and not significant.

We next ask the question whether the Law has any effect on the characteristics of admitted students. We examine whether the characteristics of students who are admitted show a discontinuity at the class rank threshold. We estimate a specification like equation (2) for all admitted students. We focus on student race/ethnicity, gender, SAT scores, and high school of origin. Columns 2-5 and 7-10 in Table 4 show the results. For both schools, admitted students just inside the top high-school decile are less likely to be male. The 10% rule leads has a stronger effect on the admissions of female students. At the same time, we find no differences in the SAT test score performance for students admitted under that law versus those admitted by the committee. For UT, we find an increase in the minority admission rate for those slightly above the threshold, which is evidence that, to some degree, the Top 10% Law promotes diversity at UT. Also at UT, we observe a slight increase of diversity in admissions along another dimension. Students that did not graduate from a feeder high-school are more likely to be admitted to UT based on the law.[6]

[6] We show in Table 3A in the appendix that these results are similar with alternative bandwidths.

Responses to the Law 3: Student Enrollment Decisions

We next examine student enrollment decisions. In Columns 1 and 6 of Table 5, we examine the differences in enrollment probabilities conditional on admission between students with and without and admissions guarantee. At A&M, students with the admissions guarantee are more likely to accept the admissions offer. While at UT the student with an admissions guarantee are less likely to enroll than students just outside the top 10%. One possible explanation for this pattern is that students in the top 10% use UT as their backup plan. If they are admitted at a preferred school they do not enroll at UT. Students in the top 10% who apply to A&M are more likely to plan on enrolling at A&M.

The effect of the admissions guarantee on enrollment unconditional on admission depends on the combined effects on application, admission and acceptance. Columns (3) and (6) in Table 2 show that for both UT and A&M the admissions guarantee leads to an increase in enrollment. Column (9) reveals that it simultaneously reduces the enrollment of students at private universities.

We next ask whether the policy is successful in diversifying the composition of enrolling students. We estimate equation (2) for enrolled students with minority status as the dependent variable. Columns (2) and (7) of Table 5 reveal that the point estimates for a jump of minority status at the cutoff are positive for A&M and even more so for UT, though since the results are not statistically significant, we are not able to offer definitive evidence that the Law increases diversity at UT or A&M. We find no effect of the law on student test scores – columns (3) and (8). The law reduces the share of males enrolling at both schools – columns (4) and (9). It reduces the share of students from feeder high-schools – columns (5) and (10).

Responses to the Law 4: Student Outcomes in College

Finally, we evaluate whether there is any evidence suggesting the Law creates "mismatch" by admitting students who are under prepared for college. We do this by comparing

the college performance of students above the threshold, and thus admitted automatically, versus those slightly below the threshold. We estimate equation (2) for all enrolled students with various college achievement outcomes as the dependent variable.

We consider five outcomes, including first semester GPA, fourth semester GPA, fourth semester persistence in college, college major, and four-year graduation rates. The results are displayed in Table 6.[7]

At UT the results again suggest very small, statistically insignificant differences in three of the five outcomes. There is a small reduction in four year persistence rates for students with guaranteed admission – students admitted due to the 10% rule are slightly more likely to drop out. Moreover, we find some evidence that UT students with guaranteed admission tend to choose "easier" majors (where we measure "difficulty" of major by the mean GPA of the major).

At TAMU, the results suggest no detectable differences in four of the five outcomes. We find a positive effect on four year graduation rates – students with guaranteed admission are more likely to graduate from A&M than students admitted by the committee. At the same time we do not find evidence that A&M students with guaranteed admission pick "easier" majors. Overall, Table 6 offers very little evidence that the Law creates "mismatch".

5. Conclusions

The full set of implications of the Texas Top 10% Law and similar laws in other states are still being examined and discussed, now over 10 years after the original implementation. It is clear that the law affected the process by which high school students matriculate to universities in Texas. Overall, though, there have been competing arguments regarding some of the primary effects of the law—that it either increased racial/ethnic diversity on the flagship campuses in comparison to what would have

[7] We show in Table 6A in the appendix that these results are similar with alternative bandwidths.

happened following the judicial ban of Affirmative Action policies, or it increased the representation of "mismatched" students who attended relatively weak high schools and are crowding out more "deserving" students from higher quality high schools. Most research has used a pre/post analysis of the law to examine these issues. In this paper, we instead examine the full set of potential behavioral responses by both the students and universities following the implementation of the law by using a regression discontinuity research design. Thus, we estimate the causal effects of being granted automatic admission to the flagship universities in Texas on the likelihood of application, the likelihood of admission, the likelihood of enrollment, and college success.

Our evidence suggests that, for the marginal student affected by the law, there is little evidence of increases in diversity or increases in mismatch. Thus, overall our results do not suggest that the law is either as costly as critics suggest nor as beneficial as proponents suggest for the marginal student.

We do, however, find that the law affects student behavior. Students who are guaranteed admission to a public University of their choice are less likely to apply to competing private universities in Texas. The effect of the 10% rule on student behavior is also reflected in the finding that, conditional on admission, students with initially guaranteed admission are less likely to enroll at UT – for A&M the opposite is true.

Our results help us to understand the consequences of the Texas 10% rule. In addition they also add to our understanding of the behavioral reactions to an admissions guarantee or to reduced uncertainty in general.

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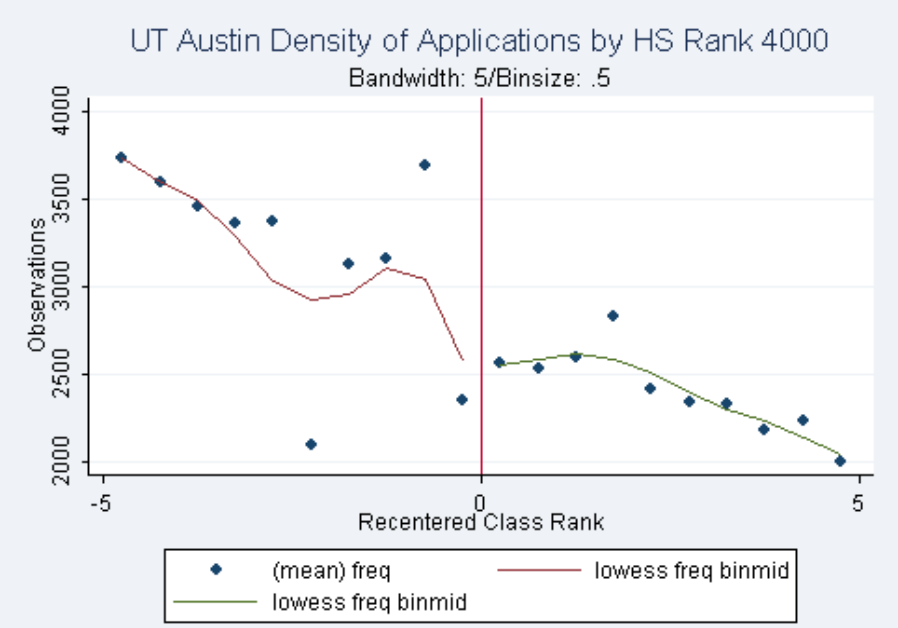
Figure 1


UT Austin Density of Applications by HS Rank 4000
Bandwidth: 5/Binsize: .5
Observations
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4000
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Recentered Class Rank
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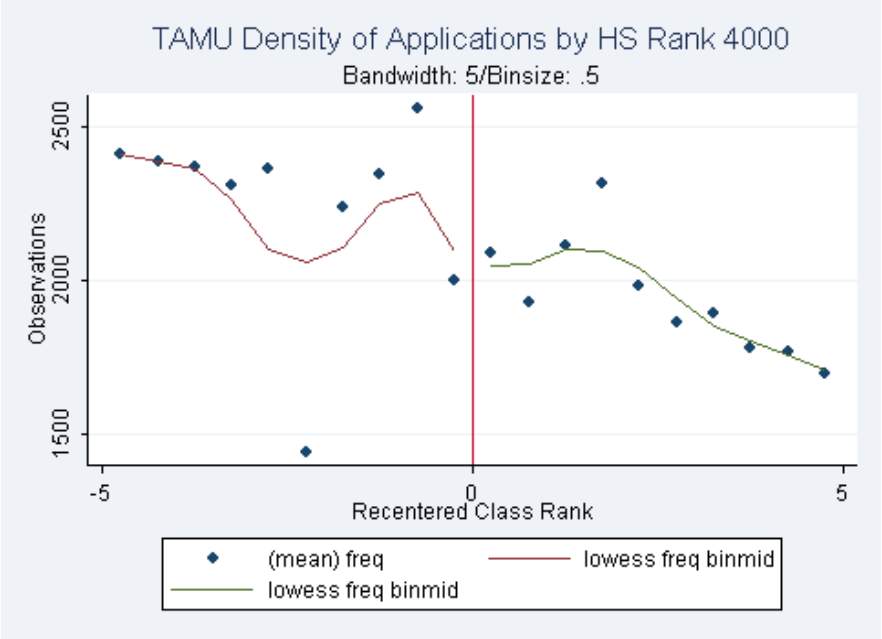
TAMU Density of Applications by HS Rank 4000
Bandwidth: 5/Binsize: .5
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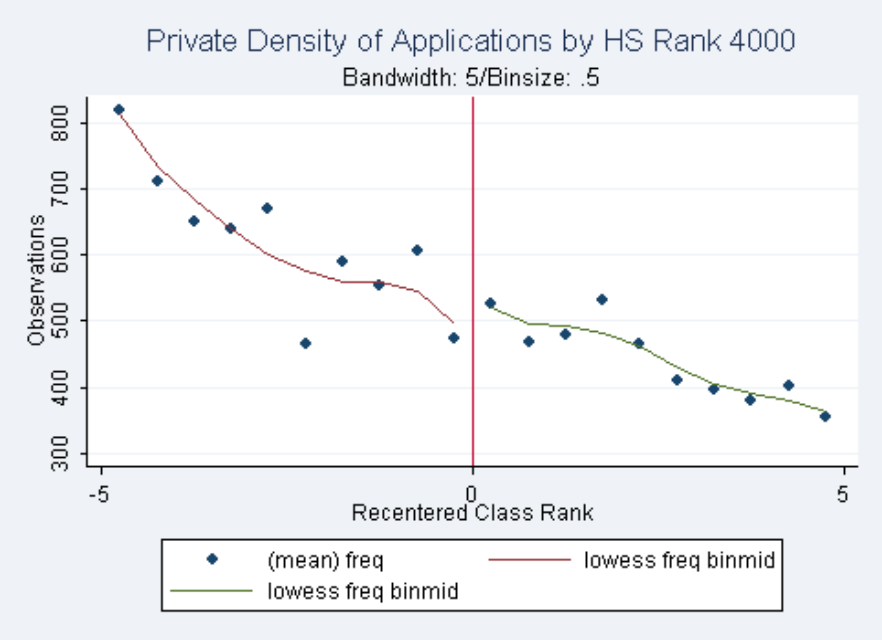
Figure 2


Private Density of Applications by HS Rank 4000
Bandwidth: 5/Binsize: .5
Observations
300
400
500
600
700
800
-5
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Recentered Class Rank
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Table 1
Descriptive Statistics

	UT-Austin					A&M				
Variable	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max
Admit	18857	0.88	0.32	0	1	16626	0.93	0.25	0	1
Enroll	18857	0.55	0.50	0	1	16626	0.59	0.49	0	1
Minority	18806	0.22	0.41	0	1	16623	0.15	0.35	0	1
SAT Score	18780	1181.71	153.88	540	1600	16616	1144.07	139.07	560	1600
Male	18853	0.45	0.50	0	1	16623	0.44	0.50	0	1
Feeder High School	18857	0.19	0.39	0	1	16626	0.15	0.36	0	1
Minority|Admit	16564	0.21	0.40	0	1	15513	0.15	0.35	0	1
Male|Admit	16607	0.45	0.50	0	1	15514	0.44	0.50	0	1
SAT Score|Admit	16610	1193.91	150.74	560	1600	15513	1147.87	139.13	560	1600
Feeder|Admit	16611	0.20	0.40	0	1	15516	0.15	0.36	0	1
Minority|Enroll	10398	0.20	0.40	0	1	9767	0.12	0.33	0	1
Male|Enroll	10410	0.45	0.50	0	1	9768	0.44	0.50	0	1
SAT Score|Enroll	10410	1187.11	148.18	560	1600	9765	1136.89	132.65	560	1580
Feeder|Enroll	10410	0.21	0.41	0	1	9768	0.14	0.35	0	1
First Semester GPA	10383	3.04	0.78	0	4	9766	2.75	0.73	0	4
Fourth Semester GPA	7399	3.06	0.56	0.8333	4	8682	2.92	0.52	1.06	4
Fourth Semester Persistence	10371	0.71	0.45	0	1	9763	0.89	0.31	0	1
4-Year Graduation	6738	0.33	0.47	0	1	9258	0.22	0.41	0	1
GPA in Chosen Major	10383	2.91	0.28	2.30	3.64	9766	2.87	0.26	2.00	3.34
Rank of Chosen Major	10383	26.39	14.42	2	49	9766	24.70	11.18	1	41

Table 2
Frequency of Applications by High School Class Rank

	UT			A&M			Private		
	(1) Application	(2) Admission	(3) Enrollment	(4) Application	(5) Admission	(6) Enrollment	(7) Application	(8) Admission	(9) Enrollment
Recentered Class Rank	-123.117***	-137.724***	-74.091***	-89.985***	-131.490***	-71.368***	-34.746***	-15.701***	-3.722***
	(11.151)	(8.396)	(4.496)	(9.781)	(8.659)	(6.636)	(2.102)	(1.303)	(0.814)
10% Rank Dummy	**143.518**	**403.098*** **	**195.007** **	**-3.817**	**118.861**	**160.712*** **	**-57.475*** **	**-39.652*** **	**-10.505** **
	(150.044)	**(144.668)**	**(83.824)**	**(81.677)**	**(77.750)**	**(49.933)**	**(18.307)**	**(9.248)**	**(4.360)**
Dummy X Class Rank	-40.720	-34.791	-17.444	43.847**	78.188***	44.146***	-28.375***	-12.118***	-6.998***
	(39.360)	(38.098)	(21.878)	(20.698)	(19.768)	(12.660)	(5.714)	(3.120)	(1.337)
Constant	2,731.257***	2,291.773***	1,385.634***	2,186.215***	2,009.015***	1,187.666***	533.732***	291.259***	98.814***
	(40.297)	(30.092)	(17.812)	(39.575)	(34.977)	(26.162)	(7.722)	(4.490)	(2.789)
Observations	57180	57180	57180	42710	42710	42710	10895	10895	10895
R-squared	0.697	0.814	0.777	0.473	0.722	0.743	0.865	0.786	0.716

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3
Discontinuities in Applicant Characteristics

	UT				A&M			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Minority	Test Score (Std)	Male	Feeder HS	Minority	Test Score (Std)	Male	Feeder HS
Recentered Class Rank	-0.002	0.005	0.006	0.006	-0.006*	-0.013	0.003	0.009**
	(0.004)	(0.009)	(0.004)	(0.004)	(0.004)	(0.010)	(0.005)	(0.004)
Top 10% Rank Dummy	**0.000**	**0.013**	**0.008**	**-0.022***	**-0.005**	**-0.080****	**0.004**	**-0.019**
	(0.012)	**(0.026)**	**(0.013)**	**(0.012)**	**(0.011)**	**(0.032)**	**(0.015)**	**(0.013)**
Interaction	0.001	-0.048***	-0.002	-0.004	0.005	-0.055***	0.005	-0.006
	(0.005)	(0.011)	(0.006)	(0.006)	(0.004)	(0.014)	(0.007)	(0.006)
Constant	0.221***	-0.065***	0.441***	0.202***	0.154***	0.013	0.449***	0.151***
	(0.010)	(0.019)	(0.010)	(0.008)	(0.008)	(0.024)	(0.012)	(0.009)
Observations	18806	18780	18853	18857	17503	17495	17504	17507
R-squared	0.000	0.004	0.000	0.002	0.000	0.007	0.001	0.004
AIC	33118	1709	26357	35225	36308	2856	24476	36610
Stata AIC	20247	51582	27142	18284	13359	46789	25194	13069

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4
Discontinuities in Characteristics of Admitted Students

	UT					A&M				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Admit	Minority	Test Score (Std)	Male	Feeder HS	Admit	Minority	Test Score (Std)	Male	Feeder HS
Recentered Class Rank	-0.020***	-0.008*	0.007	0.023***	0.010**	-0.047***	-0.008**	0.003	0.003	0.012***
	(0.005)	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.003)	(0.006)	(0.013)	(0.004)
Top 10% Rank Dummy	**0.170*** **	**0.022* **	**-0.002**	**-0.124*** **	**-0.042*** **	**0.045*** **	**-0.002**	**0.001**	**-0.104*** **	**-0.018**
	(0.013)	**(0.012)**	**(0.015)**	**(0.027)**	**(0.012)**	**(0.014)**	**(0.010)**	**(0.016)**	**(0.038)**	**(0.013)**
Interaction	0.016***	0.008	-0.002	-0.066***	-0.008	0.048***	0.007*	0.005	-0.071***	-0.009*
	(0.005)	(0.005)	(0.006)	(0.011)	(0.006)	(0.005)	(0.004)	(0.008)	(0.016)	(0.006)
Constant	0.792***	0.198***	0.453***	0.082***	0.226***	0.947***	0.152***	0.452***	0.037	0.151***
	(0.012)	(0.009)	(0.012)	(0.019)	(0.009)	(0.014)	(0.008)	(0.012)	(0.030)	(0.009)
Observations	18857	16564	16607	16610	16611	17507	16314	16316	16314	16318
R-squared	0.112	0.002	0.001	0.004	0.007	0.096	0.001	0.001	0.005	0.005

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5
Discontinuities in Characteristics of Enrolled Students

	UT					A&M				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Enroll	Minority	Test Score (Std)	Male	Feeder HS	Enroll	Minority	Test Score (Std)	Male	Feeder HS
Recentered Class Rank	-0.005	-0.009	0.004	0.034***	0.019***	0.001	-0.005	0.008	-0.002	0.013***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.005)	(0.005)	(0.004)	(0.006)	(0.016)	(0.004)
Top 10% Rank Dummy	**-0.063*** **	**0.023**	**-0.004**	**-0.080** **	**-0.028***	**0.038** **	**0.011**	**0.008**	**-0.103***	**-0.017**
	(0.016)	**(0.015)**	**(0.019)**	**(0.037)**	**(0.016)**	**(0.015)**	**(0.012)**	**(0.019)**	**(0.053)**	**(0.015)**
Interaction	-0.003	0.011	0.002	-0.069***	-0.014**	0.000	0.008	0.002	-0.074***	-0.015**
	(0.007)	(0.007)	(0.008)	(0.015)	(0.006)	(0.006)	(0.005)	(0.009)	(0.020)	(0.006)
Constant	0.658***	0.193***	0.460***	0.013	0.221***	0.608***	0.120***	0.441***	-0.049	0.135***
	(0.013)	(0.012)	(0.013)	(0.023)	(0.011)	(0.013)	(0.008)	(0.015)	(0.042)	(0.011)
Observations	16611	10398	10410	10410	10410	15516	9998	10000	9996	10000
R-squared	0.002	0.002	0.001	0.003	0.009	0.001	0.001	0.001	0.007	0.004
AIC	26559	19127	14521	1722	18787	22595	22443	14014	2668	21387
Stata AIC	26951	10377	15018	27817	10752	21433	5926	14361	25696	6988

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6
Discontinuities in College Performance Measures

	UT						A&M					
	(1) 1st GPA	(2) 4th GPA	(3) 4th Persist	(4) 4-Year Grad	(5) Mean GPA of Major	(6) Rank of Major	(7) 1st GPA	(8) 4th GPA	(9) 4th Persist	(10) 4-Year Grad	(11) Mean GPA of Major	
Recentered Class Rank	-0.003	-0.005	0.017***	-0.012	-0.002	-0.211	-0.007	-0.005	0.004	0.001	-0.007**	-0
	(0.010)	(0.008)	(0.006)	(0.012)	(0.004)	(0.195)	(0.012)	(0.007)	(0.005)	(0.004)	(0.004)	
Top 10% Rank Dummy	**-0.024**	**-0.020**	**-0.036****	**-0.029**	**-0.017***	**-1.016****	**-0.004**	**0.013**	**0.007**	**0.046*****	**0.002**	
	(0.029)	**(0.023)**	**(0.017)**	**(0.035)**	**(0.010)**	**(0.459)**	**(0.039)**	**(0.023)**	**(0.013)**	**(0.013)**	**(0.011)**	
Interaction	-0.042***	-0.029***	-0.023***	-0.005	-0.017***	-0.872***	-0.037**	-0.029***	-0.010*	-0.007	-0.003	
	(0.012)	(0.010)	(0.008)	(0.014)	(0.005)	(0.232)	(0.016)	(0.010)	(0.005)	(0.006)	(0.005)	
Constant	3.000***	3.031***	0.716***	0.574***	2.894***	25.747***	2.713***	2.879***	0.873***	0.178***	2.863***	2
	(0.024)	(0.017)	(0.013)	(0.028)	(0.008)	(0.367)	(0.031)	(0.019)	(0.012)	(0.011)	(0.007)	
Observations	10383	7399	10371	3839	10383	10383	9998	8887	9995	9759	9766	
R-squared	0.005	0.006	0.004	0.002	0.006	0.008	0.007	0.011	0.001	0.005	0.006	

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Appendix Tables

Table 1A

	UT Full Sample			UT Analysis Sample			TAMU Full Sample			TAMU Analysis Sample	
Variable	Obs	Mean	Std.	Obs	Mean	Std.	Obs	Mean	Std.	Obs	Mean	Std.
Admit	73427	0.73	0.44	18857	0.88	0.32	68397	0.73	0.45	16626	0.93	0.25
Enroll	73427	0.46	0.50	18857	0.55	0.50	68397	0.46	0.50	16626	0.59	0.49
Minority	73191	0.22	0.41	18806	0.22	0.41	68363	0.15	0.36	16623	0.15	0.35
SAT Score	73015	1182.64	163.34	18780	1181.71	153.88	68295	1136.38	150.52	16616	1144.07	139.07
Male	73378	0.48	0.50	18853	0.45	0.50	68376	0.50	0.50	16623	0.44	0.50
Feeder High School	73427	0.23	0.42	18857	0.19	0.39	68397	0.20	0.40	16626	0.15	0.36
Minority|Admit	53561	0.20	0.40	16564	0.21	0.40	49593	0.15	0.36	15513	0.15	0.35
Male|Admit	53701	0.47	0.50	16607	0.45	0.50	49609	0.48	0.50	15514	0.44	0.50
SAT Score|Admit	53722	1217.21	157.29	16610	1193.91	150.74	49602	1164.90	146.88	15513	1147.87	139.13
Feeder|Admit	53724	0.23	0.42	16611	0.20	0.40	49617	0.18	0.38	15516	0.15	0.36
Minority|Enroll	33447	0.19	0.40	10398	0.20	0.40	31252	0.12	0.33	9767	0.12	0.33
Male|Enroll	33494	0.48	0.50	10410	0.45	0.50	31259	0.48	0.50	9768	0.44	0.50
SAT Score|Enroll	33494	1203.62	151.75	10410	1187.11	148.18	31252	1152.35	139.81	9765	1136.89	132.65
Feeder|Enroll	33494	0.24	0.43	10410	0.21	0.41	31259	0.17	0.38	9768	0.14	0.35
First Semester GPA	32829	3.06	0.82	10383	3.04	0.78	31252	2.76	0.79	9766	2.75	0.73
Fourth Semester GPA	24158	3.08	0.59	7399	3.06	0.56	27580	2.94	0.56	8682	2.92	0.52
Fourth Semester Persistence	32781	0.74	0.44	10371	0.71	0.45	31241	0.88	0.32	9763	0.89	0.31
4-Year Graduation	27779	0.27	0.44	6738	0.33	0.47	38895	0.17	0.37	9258	0.22	0.41
GPA in Chosen Major	32829	2.92	0.28	10383	2.91	0.28	31252	2.86	0.28	9766	2.87	0.26
Rank of Chosen Major	32829	26.99	14.38	10383	26.39	14.42	31252	24.27	11.57	9766	24.70	11.18