NBER WORKING PAPER SERIES

TRACING THE EFFECTS OF GUARANTEED ADMISSION THROUGH THE COLLEGE PROCESS: EVIDENCE FROM A POLICY DISCONTINUITY IN THE TEXAS 10% PLAN

Jason Fletcher
Adalbert Mayer

Working Paper 18721
http://www.nber.org/papers/w18721

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2013

We thank Rodney Andrews, Dawn Koffman, Lance Lochner, Mark Long, Sunny Niu, Steven Puller and Marta Tienda for helpful comments. This research uses data from the Texas Higher Education Opportunity Project (THEOP) and acknowledges the following agencies that made THEOP data available through grants and support: Ford Foundation, The Andrew W. Mellon Foundation, The William and Flora Hewlett Foundation, The Spencer Foundation, National Science Foundation (NSF Grant # SES-0350990), The National Institute of Child Health & Human Development (NICHD Grant # R24 H0047879) and The Office of Population Research at Princeton University. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Tracing the Effects of Guaranteed Admission through the College Process: Evidence from a Policy Discontinuity in the Texas 10% Plan
Jason Fletcher and Adalbert Mayer
NBER Working Paper No. 18721
January 2013
JEL No. I21,I23,I28

ABSTRACT

The Texas 10% law states that students who graduated among the top 10% of their high school class are guaranteed admission to public universities in Texas. We estimate the causal effects of this admissions guarantee on a sequence of connected decisions: students' application behavior, admission decisions by the university, students' enrollment choices conditional on admission; as well as the resulting college achievement. We identify these effects by comparing students just above and just below the top 10% rank cutoff. While this design is in the spirit of a regression discontinuity, we note important differences in approach and interpretation. We find that students react to incentives created by the admissions guarantee - for example, by reducing applications to competing private universities. The results also suggest that the effects of the admissions guarantee depend on the university and the type of students it attracts, and that the law is binding and alters the decisions of the admissions committees. We find little evidence that the law increases diversity or leads to meaningful mismatch for the marginal student admitted.

Jason Fletcher
Yale School of Public Health
Department of Health Policy and Management
60 College Street, #303
New Haven, CT 06520
and NBER
jason.fletcher@yale.edu

Adalbert Mayer
Department of Economics
Washington College
Chestertown, MD 21620
amayer2@washcoll.edu

1. Introduction

The Texas 10% law states that a student who graduates among the top 10% of her high school class is guaranteed admission to public universities in Texas. Consequently, students just inside the top 10% and students just outside the top 10% are treated differently in the college admissions process. This leads to different incentives for the two groups of students and different treatment of these students by the admissions committees at the schools. Ultimately, the differential treatment by the law and the resulting choices can lead to differences in educational outcomes.

In this paper, we examine the effects of the 10% rule on a sequence of connected decisions: students' application behavior, admission decisions by the university, students' enrollment choices conditional on admission; as well as the resulting college achievement. Intuitively, our identification strategy amounts to comparing students just above and just below the top 10% high school class rank cutoff. We examine if we are able to detect a discrete jump in probabilities of application, admission, or enrollment at the top 10% cutoff. Then, we look for discontinuities in student performance conditional on these decisions.

We make two contributions. First, we estimate the behavioral consequences of an admissions guarantee. Second, under the assumption that the total number of slots at a university is fixed (in the short term) we can contribute to the evaluation of the 10% rule by comparing the marginal student enrolled due to the rule to the marginal student not enrolled due to the rule.

We use complete administrative data from 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 applications to a specific flagship university. We do find some limited evidence that the law affects the characteristics of applicants. For example, the admissions guarantee seems to encourage students with lower SAT scores to apply to Texas A&M. At UT it leads to slightly more applicants from high schools that traditionally do not send many students to the university, suggesting a broadening of the applicant pool related to the law. Our results also suggest spillover effects on applications to institutions not covered by the law. The admissions guarantee to public universities leads to a drop in applications to private universities (Rice and SMU), suggesting that guaranteed admission at UT or A&M makes applications to the private schools less valuable.

We are able to show that the 10% law is binding and does alter admissions decisions conditional on application – 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% acceptance rate at UT and a 95% rate at A&M.

On the margin, the admissions guarantee changes the characteristics of the admitted students conditional on application. At UT it leads to more admissions of students from ethnic minorities and from high schools that traditionally provide few students to the university. At both universities it leads to the admission of more female students. In contrast, we find no differences in the SAT test score performance for students admitted with or without admissions guarantee.

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, which suggests that the admissions guarantee leads to applications of students for whom A&M is the preferred school among their eventual options. At UT the result is reversed. It is possible that students in the top 10% of their high school use UT as their backup plan—a “high quality safety school” with guaranteed admission. If they are admitted at a preferred school, they do not enroll at UT.

Next, we look at the students who eventually enroll at A&M or UT. Holding the total number of university students fixed, on the margin the 10% rule leads to the enrollment of students in the top 10% at the expense of students below the top 10%. The law helps to increase diversity if enrolled students just inside the top 10% of their high school are more likely to be members of a minority than students just outside the top 10%. If the students just inside the top 10% are less well prepared they are expected to perform less well – the 10% rule induces "mismatch".

At both universities, the marginal student from the top 10% of her high school class is more likely to be female and less likely from a feeder high school (those with histories of sending students to the university). We find some weak evidence that the 10% rule increases minority enrollment at UT, otherwise we cannot detect differences in the characteristics between enrolled students who graduated just inside or just outside the top high school decile. At A&M there is no evidence that students with a prior admissions guarantee perform worse than similar students without guaranteed admission. At UT we find mixed evidence. Students from the top high school decile tend to choose easier majors[1] and are slightly less likely to stay enrolled for more than 3 years, but we find no evidence of an effect on GPA.

With these general findings outlined, we now consider how the law could affect individuals along the multiple decisions we examine, discuss the data and empirical design, present our full set of results and robustness checks, and conclude.

2. Background of the Law and Related Research

[1] Where "difficulty" of a major is measured by the mean GPA of the major.

Policy makers have a history of attempting to broaden access to higher education and to increase the enrollment of minorities at colleges and universities.[2] But a consensus about the appropriate policies to achieve these goals has not been reached. Race based admissions policies, such as affirmative action, have been challenged in court and it is not clear what their role will be in the future.[3] In this paper, we evaluate a policy that attempts to broaden access to higher education and to increase minority enrollment, and was implemented in part as a substitute for race based admissions policies.

The 1996 Hopwood decision by the 5th Circuit Court required Texas universities to discontinue the use of race as an admissions criterion. One response was the "Texas top 10% law", established when Governor George W. Bush signed Texas House Bill 588 into law on May 20th 1997.

The law states that:

> "*Each general academic teaching institution shall admit an applicant for admission to the institution as an undergraduate student if the applicant graduated in one of the two school years preceding the academic year for which the applicant is applying for admission from a public or private high school in this state accredited by a generally recognized accrediting organization with a grade point average in the top 10 percent of the student's high school graduating class.*"[4]

---

[2] See Bowen and Bok (1988) for a detailed discussion.

[3] Supreme Court decisions on the issue include the 1978 Regents of the University of California v. Bakke decision that allowed the use of Race only as one many factors in the admissions process, and the 2003 Gratz v. Bollinger and Grutter v. Bollinger rulings that prevent public universities from giving automatic advantages based on race or ethnicity but allow the consideration of race and ethnicity when assessing individuals on a case by case basis. Currently, the Supreme Court has agreed to hear a case that challenges the policy of the University of Texas to consider race in the admissions process of those not covered by the 10% law discussed here.

[4] Where general academic teaching institution refers to the public universities and colleges in Texas (see section 61.003 of the Texas education code).

The Texas House Research Organization Bill Analysis of HB 588 (1997) documents that its proponents argued that due to the level of segregation at Texas high schools the policy "would provide a diverse population and ensure that a large, well qualified pool of minority students was admitted to Texas universities." Proponents wanted to "establish a fair, race-neutral admissions structure providing students from all backgrounds and parts of the state an opportunity to continue their educations." Opponents were concerned that the law could distort the admissions process and argued that "Universities should retain the authority to make such decisions and implement policies that best suit their individual needs and that will best help them meet their goals and educate their student bodies."

Partly due to the controversies with the law's passage, several empirical evaluations of the 10% law have been conducted across a number of disciplines. One key focus of research has been in examining whether the law changed the proportion of minority students at flagship campuses in Texas. A second focus has been on whether the students who attend these universities due to admission guarantees experience worse college outcomes, due to potential mismatch of students to universities. The general findings suggest that minority enrollment increased due to the law but not to the levels before the affirmative action ban in 1997.[5] Few studies have supported claims of "mismatch": the admission of less well prepared students from inside the top decile at the expense of better prepared students from outside the top decile.[6] Several papers suggest that the admissions guarantee has increased applications from students in the top decile of their high schools and widened the pool of high schools that provide these applicants.[7] A common empirical strategy of these studies has been a pre/post analysis – the

[5] Bucks (2004), Harris and Tienda (2010), Koffman and Tienda (2008), Long and Tienda (2008), Andrews et al. (2010)
[6] Cortes (2010), Furstenberg, (2010)
[7] Long, Saenz, and Teinda (2010), Long and Tienda (2010), Montejano (2001)

downside of this approach is that other factors may change simultaneously with the implementation of the law. We use a different identification strategy, which relies on the discontinuity introduced by the law and thus makes comparisons between students in the post-Top 10% Law regime who all face the same rules. Our strategy thus provides complementary evidence with previous research that used pre/post analysis.

In a separate branch of the literature, several researchers have used the Top 10% Law in a regression discontinuity (RD) framework. They primarily focus on estimating the "treatment" of attending a more selective college on later outcomes, such as college success (Cortes, 2010 and Furstenberg, 2010) and post-college wages. Thus, these papers focus on the "treatment" of attending a selective college versus the "control group" who attended a less selective college due to the Top 10% law.

In the current paper and in Tienda and Niu (2010) an alternative framework is used to investigate a different "treatment": guaranteed admission due to a students' high school rank. Tienda and Niu utilize survey data of Texas high school graduates and find that the 10% rule increases overall college enrollment of students from the top 10% of their high school. Moreover, it increases enrollment of eligible Hispanic students and students from predominately minority high schools at the University of Texas and Texas A&M University.

In this paper, we use the policy discontinuity to examine multiple connected behavioral changes induced by the admissions guarantee. However, our paper does not use a traditional RD design. Instead, we leverage the notion of an underlying continuous distribution of individuals based on high school rank who are treated differently during several aspects of the college decision process based on a policy discontinuity. In this way, we analyze the effects of the admission guarantee on application, admission, and enrollment. Finally, we examine the implications for student performance in college. Thus, our paper does not evaluate the effects of attending a selective college (i.e. the RD literature in this area) and it goes beyond the evaluation of the effects of the 10% law on enrollment (i.e. many of the pre/post analyses). Instead it more comprehensively evaluates the multiple potential effects of the admissions guarantee on a series of related decisions that affect higher education outcomes using a common empirical framework.

3. Potential Effects of the guaranteed college admission

The 10 % rule mandates that students who graduate in the top 10% of their high school classes are guaranteed admission by any state university in Texas. This leads to differences in incentives between students who graduated in the top 10% of their high school and students who graduated just below the top 10%; potentially resulting in differences in application and enrollment patterns, as well as differences in academic achievement between these two groups.

Application

Students in the top 10% of their high school class know that their admission to a state school in Texas is guaranteed. This guarantee 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, which reduces the benefit to applying to other schools – these other schools could be less preferred state schools or private universities. Additionally, a student with high test-scores has a high probability of admission without an admission guarantee, so that the guarantee could affect her 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 composition of admitted students depends on the decision to apply and admission conditional on application. The 10% law affects admissions directly by mandating that all students in the top 10% of their high school classes must be admitted and indirectly by changing the composition of applicants. Students outside the top 10% continue to be admitted at the discretion of the admissions committees of the universities.

First, we ask whether the law is binding in general, or would the students in the top 10% of their high school classes have been admitted anyway? We address this question by comparing the admissions probabilities of students in the 90^{th} and 89^{th} high school percentiles, conditional on application.

Second, we ask more specifically, does the law change the composition of admitted students – conditional on application? To isolate the marginal effects of the law on student characteristics we compare the characteristics of admitted students just inside the top decile to students just outside the top decile. The composition of admitted students just outside of top 10% reflects the preferences of the admissions committee. Without the law, some of the students in the top 10% might not be admitted if their characteristics differ from those valued by the committee. Holding the total number of university students fixed, on the margin the 10% rule leads to the enrollment of students in the top 10% at the expense of students just below the top 10%.

Enrollment

The eventual enrollment depends on the decision to apply, the admission decision by the committee, and the decision to enroll, conditional on application and admission. First, we examine the decisions made by students to accept admission. Theoretically, the effect is ambiguous – the admissions guarantee might induce students to only apply to their preferred school and enroll at that school so that the effect of the law is to increase enrollment rates, conditional on acceptance. Another possibility is that the admissions guarantee makes a state school valuable to insure against non-admission at a preferred non-state school. That is, it provides a "safety school" of high quality. This could lead to lower rates of enrollment conditional on acceptance.

To study the marginal effect (the result of application, admission and acceptance) of the law on the composition of the student body at the two flagship schools we consider enrolled students and compare the characteristics of students who graduated just inside the top 10% of their high school class to the characteristics of students just outside the top 10%. If students just inside the top 10% are more likely to be member of a minority than students just outside the top 10%, the policy increases diversity.

College Achievement

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%, we can infer that the policy leads to mismatch. Mismatch could happen for a number of reasons; for example, high school rank could be a worse predictor of college performance than the index of characteristics considered by an ordinary admissions process. On the other hand, if the ordinary admissions process places too large a weight on SAT scores and/or other characteristics such as legacy status and too small a weight on high school class rank, the policy could provide lower mismatch.

4. Data

In order to examine the effects of the law, we use administrative data from several public and private universities in Texas. Because the law only applies to Texas residents, we focus our analysis on these students. We focus on the flagship institutions: the University of Texas-Austin and Texas A&M University, though we also examine potential spillover effects on Rice University and SMU. These data were collected under the auspices of the Texas Higher Education Opportunity Project, and we focus on data collected during the years of the Top 10% law (1999-2002).[8]

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 top 10% cutoff are 89% at UT and 94% at TAMU; the

[8] 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 http://theop.princeton.edu/index.html

appendix table shows the rates for the full sample of applicants is 73% for each school. Unconditional enrollment rates are approximately 58-60% of all applicants. Minority (African American/Hispanic) students make up 23% of applicants at UT and 15% at TAMU. Students from "feeder" high schools comprise 21% of UT applicants and 15% of TAMU applicants. The average SAT score for UT applicants was 1189 and 1146 at TAMU. The table also presents these summary statistics conditional on admission and enrollment decisions. Finally, descriptive statistics are shown for several college success measures, including GPA, persistence, graduation rates, and choice of major.

5. Empirical Specifications and Results

Our empirical strategy is to compare students "close" to a 90th-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.

Our identification strategy relies on the notion that students who are ranked in the 89th percentile in their graduating class provide a good counterfactual to students ranked in the 90th percentile. In order for this assumption to be valid, high school student characteristics should be continuous through the threshold.[9]

We also assume that each percentile of high school graduates contains the same number of individuals. This assumption technically holds by definition and allows us to use data on applications only. We do not require the data on all high school graduates. However, since the

[9] We highlight again here that the student characteristics that should be continuous through the threshold are the population of high school students from the state of Texas, not necessarily the population of students who have applied to universities in Texas. Indeed, the latter is a test of the policy rather than a test of the research design.

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. Tienda and Niu (2010) find no evidence for such a shift. They investigate survey data covering all high school graduates and report "… no significant 'clumping' around the 10th percentile [the 90th percentile in our terminology] class rank." If selective reporting does lead to a shift of the distribution from outside the top 10% into the top 10% we would – ceteris paribus – observe more college applications with high school ranks just inside the top 10% than just outside the top 10%.

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. We briefly discuss potential effects at each stage in turn[10].

Responses to the Law 1: Student Application Patterns

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

In order to examine the application patterns in the data, we define 1/10th of a percentile bins for the high school rank and count the number of applicants in each bin. As mentioned above we assume that the number of high school graduates in each bin is continuous at the 90th percentile in the high school class rank distribution, where the top 10% law is implemented (i.e., the number of graduates between the 89.9th and 90th percentile is equal to the number of

[10] We also note that our analysis is potentially missing a "pre-application" stage, where students might be able to shift their effort levels in high school in order to qualify for guaranteed admission. Our results should be viewed with this caveat in mind.

graduates between the 90th and 90.1th percentile). Our second assumption is that without the top 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 top 10% rule.

Figure 1 displays the raw data as well as a lowess smoother of the number of applicants by 1/2 percentile bins between the 85th and 95th percentiles, centered at the 90th percentile. The figure shows the results for UT-Austin on top and for Texas A&M on the bottom. For either school, there is some evidence of increases in application rates slightly above the 90th percentile (particularly at the 91st percentile).

To formally investigate whether the number of applicants jumps at the 90th percentile we use a local 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, *c* indicates the class-rank cutoff, $g(.)$ 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. Following Lee and Card (2008), standard errors are clustered on the running variable (high school rank). For both universities, we find evidence of increases in application rates due to the admissions guarantee, though the increase at UT is not precisely estimated[11]. Note again that, although we only have data on applications (and not those who did not apply), our test of the effects of the Top 10% plan on applicant behavior is based on our assumption of an underlying continuous set of individuals who *could* apply. This assumption follows from the fact that each percentile of high school graduates

[11] We find increases in the number of students in the bins of approximately 120 (UT) and 200 (TAMU), where the bin-sizes are 526 students at UT and 423 students at TAMU.

contains the same number of individuals and technically holds by definition, allowing us to use data on applications only. [12]

As we discuss above, the law could also have spillover effects on other universities. For example, 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 several 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 for each 1/2 percentile below and above the 90th percentile. Estimating (1) for the private universities provides evidence of reductions for students in the top decile in their graduating class. Column (7) of Table 2 displays an 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 characteristics of applicants changes around the cutoff. In traditional RD designs, this exercise would be a test of whether the covariates are "smooth" across the threshold. However, in our case, we are not testing this smoothness assumption; rather, we are leveraging the underlying smoothness in population characteristics around this arbitrary policy discontinuity to examine whether the policy affected the distribution of the characteristics of students who applied to the universities in our database. We will interpret any changes in the characteristics as evidence of a policy effect. We estimate the following regression model:

[12] If our assumption of a uniform class rank distribution is violated and there are more students in the percentiles just inside the top 10% than outside the top 10% - the reduced need to apply to multiple universities under guaranteed admission outweighs the benefit of applying from the admissions guarantee.

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

where X_i captures a characteristic of the applicant pool. The coefficient of interest is δ, which measures whether the characteristics of applicants change 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. This suggests that students from non-feeder high schools are encouraged to apply to UT by the admissions guarantee. For A&M the point estimate for feeder schools is similar but the result is not statistically significant. For SAT test scores, we find no connection between the 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 below the threshold. We interpret this to mean that the admissions guarantee encourages students with lower SAT scores to apply to Texas A&M.[13]

Responses to the Law 2: Admission

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

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

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

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

experienced an increase in the probability of admission by 17 percentage points at UT and 4 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.

Since the total effect of the top 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 both universities. This suggests that the law is binding.

We next estimate responses by the admissions committee by examining whether the characteristics of students who are admitted show a discontinuity at the class rank threshold. Students just inside the top 10% have to be admitted due to the law. If the number of slots is fixed, this occurs at the expense of students outside the top 10%. 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 more likely to be female. Without the 10% law admissions committees would have admitted more male students—this could be a response to the growing gender imbalance favoring females at most colleges. 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 at the admissions stage. Also at UT, we observe a slight increase of diversity in admissions along another dimension: students who did not graduate from a feeder high school are more likely to be admitted to UT based on the law.[14] [15]

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 an admissions guarantee. At A&M, students with the admissions guarantee are more likely to accept the admissions offer (though this estimate is not statistically significant). 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—a "high quality safety school". If they are admitted at a preferred school they do not enroll at UT. We find the opposite result for students who apply to A&M, suggesting that the admissions guarantee leads to applications of students for whom A&M is the preferred school among their eventual options.

The effect of the admissions guarantee on overall enrollment – not conditional 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 being above the top 10% cutoff simultaneously reduces the enrollment of students at the private universities.

We next ask whether the policy is – for the marginal student - successful in diversifying the composition of enrolled students, which was one of the goals of the law. We estimate

[14] We show in Table 4A in the appendix that these results are similar with alternative bandwidths.

[15] Another way the admissions committee might respond to the Top 10% Law is to offer merit aid to students outside the top 10% who they would prefer and offer no aid to students who are guaranteed admission. We have no data on financial aid offers, so our results should be viewed with this caveat. We thank an anonymous reviewer for pointing out this limitation.

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 discontinuity in the likelihood the student is a minority at the cutoff are positive for both A&M and 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. While we find no effect of the law on student test scores (Columns 3 and 8), we find effects of reductions in male enrollees (Columns 4/9) as well as some evidence for a reduction in students from feeder high schools (Columns 5/10).

Responses to the Law 4: Student Outcomes in College

Finally, we evaluate whether there is any evidence suggesting the law creates "mismatch" by enrolling 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.[16]

At UT the results suggest very small, statistically insignificant decreases for students in the top 10% for three of the five outcomes. For the other two outcomes we find significant but small decreases. There is a small reduction in fourth semester persistence rates for students with guaranteed admission – students admitted due to the top 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).

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

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, unlike UT, we do not find evidence that A&M students with guaranteed admission pick "easier" majors. Overall, Table 6 highlights that the 10% law has different effects on the student bodies at the two flagships schools, but offers very little evidence that the law creates systematic "mismatch" for the marginal admitted student.

6. Conclusions

We exploit a difference in the economic environment of otherwise very similar individuals to examine the behavioral consequences of incentive differences on a sequence of connected decisions. 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.

We find that the Texas 10% law lives up to some of the expectations of its proponents. It affects the application behavior of high school graduates, encouraging applications to the state's flagship universities from students who did not graduate from classic feeder high schools; thereby reaching population groups that were previously underrepresented in the applicant pool. The law is binding and alters the decisions of the admissions committees. However, for the marginal student, we find little evidence that the law leads to notable increases in diversity. This confirms the finding of previous studies that the top 10% law is not able to compensate for the discontinuation of race based admissions policies. At the same time, there is little evidence that the law leads to “mismatched” students who attended relatively weak high schools and are crowding out more “deserving” students from higher quality high schools.

The law has a number of other behavioral consequences. Students who are guaranteed admission to a public university of their choice are less likely to apply to competing private universities in Texas. We also find that the behavioral consequences of the admissions guarantee depend on the university and the type of students it attracts. Conditional on eventual admission, students eligible for guaranteed admission are more likely to enroll at Texas A&M than students without initially guaranteed admission. For UT the opposite is true: students with initially guaranteed admission are less likely to enroll. One possible explanation for this pattern is that students who view A&M as their first choice are induced to apply by the admissions guarantee, while the same admissions guarantee leads students to use UT as their backup plan - if they are admitted at a preferred school they do not enroll at UT.

The future of affirmative action – and race based admission policies in general – is uncertain as policy alternatives are evaluated. One of these policy alternatives are top x-percent rules, such as the Texas 10% law. Now, over 10 years after the implementation of the law, the full set of its implication are still examined and discussed. We add to this discussion by using a novel empirical approach to reinforce the results of previous studies and comprehensively examine the various effects of the law within a fixed research design.

Our results support previous findings suggesting that the law: a) does not lead to the admission of ill-prepared students; b) increases applications from high schools that traditionally do not send many students to the state’s flagship universities; but c) is not able to achieve the ethnic diversity found before the elimination of Affirmation Action. Moreover, we uncover additional behavioral consequences; contributing to a better understanding of the sequence of decisions that lead to enrollment at a college more generally.

References

Andrews, R. J., V. Ranchhod, and V. Sathy (2010). "Estimating the responsiveness of college applications to the likelihood of acceptance and financial assistance: Evidence from Texas." Economics of Education Review 29 (1), 104 - 115.

Andrews. Rodney J. (2009) "High School Quality, Race, and College Achievement." THEOP Working Paper

Bowen, W. G. and Bok, D. (1998). "The shape of the river: Long-term consequences of considering race in college and university admissions". Princeton, NJ: Princeton University Press.

Bucks, Brian. (2004) "Affirmative Access Versus Affirmative Action: How Have Texas' Race-Blind Policies Affected College Outcomes?" mimeo

Cortes, Kalena E.(2010) "Do Bans on Affirmative Action Hurt Minority Students? Evidence from the Texas Top 10% Plan." Economics of Education Review, 29(6): 1110-1124

Furstenberg, Eric (2010) "Academic Outcomes and the Texas Top Ten Percent Law." *The ANNALS of the American Academy of Political and Social Science*, 627(1), 167-183

Harris, Angel L and Marta Tienda (2010) "Minority Higher Education Pipeline: Consequences Of Changes In College Admissions Policy In Texas." *The ANNALS of the American Academy of Political and Social Science*. 627(1): 60-81

Hopwood v. University of Texas, 78 F.3d 932 (5th Cir., 1996).

Imbens, G. W., and T. Lemieux (2008). "Regression discontinuity designs: A guide to practice." *Journal of Econometrics*, 142(2), 615-63

Koffman, Dawn and Marta Tienda (2008) "Missing in Application: The Texas Top 10% Law and Campus Socioeconomic Diversity." Princeton University Working Paper

Lee, D. S., and D. Card (2008). "Regression discontinuity inference with specification error." *Journal of Econometrics*, 127(2), 655-674.

Long Mark C. (2007). "Affirmative Action and Its Alternatives in Public Universities: What Do We Know?" *Public Administration Review*, March, 315-330.

Long, M. C., V. Saenz, and M. Tienda (2010)" Policy Transparency and College Enrollment: Did the Texas Top Ten Percent Law Broaden Access to the Public Flagships?" The ANNALS of the American Academy of Political and Social Science 627 (1), 82-105.

Long Mark C. and Marta Tienda (2008) "Winners and Losers: Changes in Texas University Admissions Post-Hopwood." *Educational Evaluation and Policy Analysis*, 30(3): 255-280

Long Mark C. and Marta Tienda (2010) "Changes in Texas Universities' Applicant Pools after the Hopwood Decision" *Social Science Research* 39(1): 48-66

Montejano, David. (2001). "Access to the university of texas at austin and the ten percent plan:a three year assessment." Technical report, University of Texas at Austin.

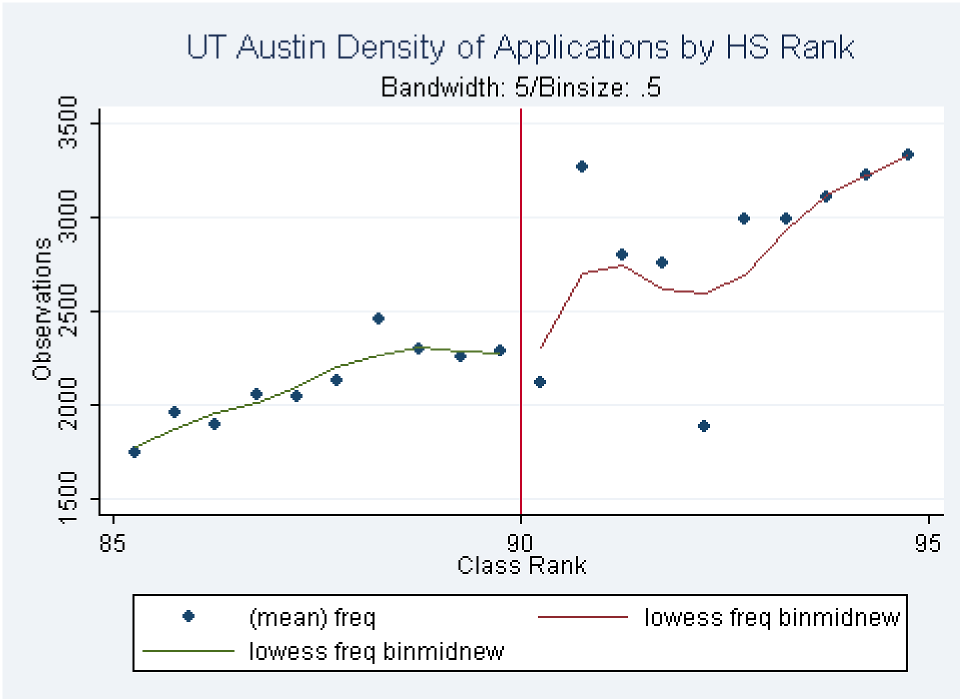
Niu, Sunny Xinchun, Teresa Sullivan, Marta Tienda, (2010) "Minority Talent Loss and the Texas Top 10 Percent Law" *Social Science Quarterly*, 89(4): 831-845

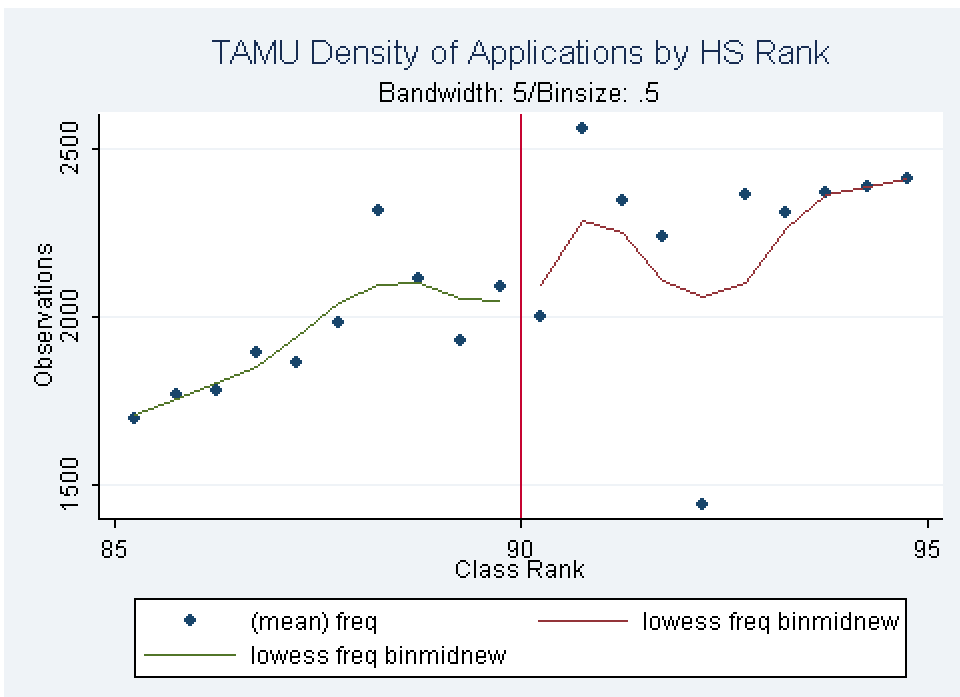
Niu, Sunny Xinchun, Marta Tienda, Kalena Cortes (2006) "College selectivity and the Texas top 10% law." *Economics of Education Review* 25(3): 259-272

Texas House Research Organization Bill Analysis of HB 588, April 15th 1997.
Available at: *http://www.lrl.state.tx.us/scanned/hroBillAnalyses/75-0/HB588.PDF*

Tienda, Marta and Sunny X. Niu (2010) "The impact of the Texas 10% law on college enrollment: Regression discontinuity approach." *Journal of Policy Analysis and Management*, 29(1): 84-110

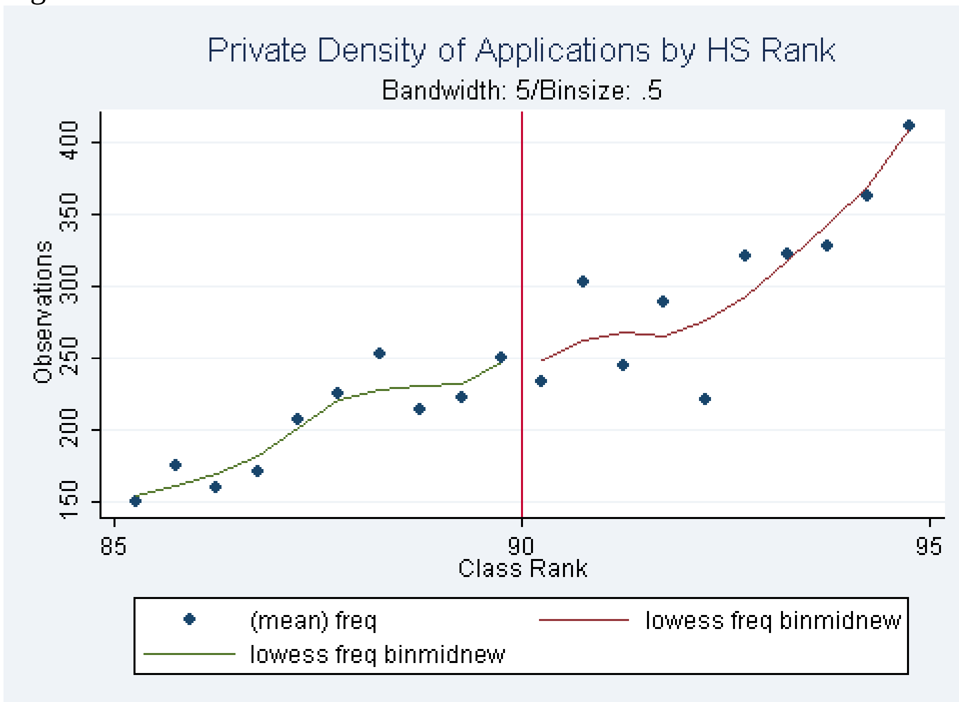
Figure 1





Notes: These figures plot the counts of students at each ½ percentile of the high school rank distribution between the 85th and 95th percentiles in the data

Figure 2



Notes: These figures plot the counts of students at each ½ percentile of the high school rank distribution between the 85th and 95th percentiles in the data

Table 1
Descriptive Statistics for Applicants to UT or TAMU
Sample of Texas Students between 85-95% High School Class Rank

	UT-Austin					A&M				
Variable	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max
Admit	17236	0.89	0.31	0	1	16023	0.94	0.23	0	1
Enroll	17236	0.58	0.49	0	1	16023	0.60	0.49	0	1
Minority	17197	0.23	0.42	0	1	16021	0.15	0.35	0	1
SAT Score	17175	1178.21	154.80	540	1600	16019	1143.03	138.57	560	1600
Male	17233	0.45	0.50	0	1	16020	0.44	0.50	0	1
Feeder High School	17236	0.21	0.40	0	1	16023	0.15	0.36	0	1
Minority|Admit	15303	0.22	0.41	0	1	15087	0.15	0.35	0	1
Male|Admit	15338	0.45	0.50	0	1	15087	0.44	0.50	0	1
SAT Score|Admit	15341	1189.88	151.50	560	1600	15088	1146.38	138.73	560	1600
Feeder|Admit	15341	0.22	0.41	0	1	15089	0.15	0.36	0	1
Minority|Enroll	9950	0.20	0.40	0	1	9633	0.12	0.33	0	1
Male|Enroll	9961	0.45	0.50	0	1	9634	0.44	0.50	0	1
SAT Score|Enroll	9961	1185.45	148.81	560	1600	9633	1136.08	132.20	560	1580
Feeder|Enroll	9961	0.22	0.41	0	1	9634	0.14	0.35	0	1
First Semester GPA	9934	3.03	0.78	0	4	9632	2.75	0.73	0	4
Fourth Semester GPA	7096	3.05	0.57	0.8333	4	8567	2.92	0.52	1.06	4
Fourth Semester Persistence	9922	0.72	0.45	0	1	9629	0.89	0.31	0	1
4-Year Graduation	6155	0.35	0.48	0	1	8927	0.22	0.42	0	1
GPA in Chosen Major	9934	2.91	0.28	2.30	3.64	9632	2.87	0.26	2.00	3.34
Rank of Chosen Major	9934	26.36	14.40	2	49	9632	24.72	11.17	1	41

Table 2

Frequency of Applications, Admission, and Enrollment by High School Class Rank

	UT			A&M			Private		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Application	Admission	Enrollment	Application	Admission	Enrollment	Application	Admission	Enrollment
Recentered Class Rank	-115.685***	-128.551***	-72.081***	-85.786***	-122.955***	-68.402***	-20.113***	-9.023***	-1.831***
	(8.919)	(6.904)	(3.835)	(8.678)	(7.487)	(6.076)	(1.286)	(0.872)	(0.363)
10% Rank Dummy	**117.954**	**378.179*** **	**182.019** **	**195.720** **	**270.318*** **	**209.837*** **	**-30.075*** **	**-24.912*** **	**-7.557*** **
	(128.566)	**(128.337)**	**(77.311)**	**(79.640)**	**(75.924)**	**(48.886)**	**(10.777)**	**(5.237)**	**(2.581)**
Dummy X Class Rank	-37.991	-30.290	-17.999	39.648*	69.653***	41.180***	-14.347***	-5.527***	-5.978***
	(33.644)	(33.582)	(20.099)	(20.200)	(19.284)	(12.376)	(3.084)	(1.584)	(0.806)
Constant	2,424.300***	2,074.269***	1,314.460***	1,986.679***	1,857.559***	1,138.541***	256.013***	130.756***	45.984***
	(31.128)	(24.906)	(15.262)	(35.178)	(30.705)	(24.104)	(4.593)	(3.035)	(1.167)
Observations	50739	50739	50739	40867	40867	40867	5217	5217	5217
R-squared	0.723	0.823	0.787	0.644	0.779	0.769	0.871	0.766	0.744

Standard errors are clustered on the running variable (high school rank). , *** p<0.01, ** p<0.05, * p<0.1

Note: Estimates are unconditional on application or admission and thus contain the same sample sizes across columns for each university

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	-0.001	0.004	0.005	0.008**	-0.007*	-0.015	0.007	0.011**
	(0.004)	(0.009)	(0.004)	(0.004)	(0.004)	(0.011)	(0.006)	(0.004)
Top 10% Rank Dummy	**0.000**	**0.007**	**0.012**	**-0.022***	**-0.007**	**-0.087****	**0.014**	**-0.018**
	(0.012)	**(0.027)**	**(0.013)**	**(0.013)**	**(0.011)**	**(0.035)**	**(0.016)**	**(0.015)**
Interaction	0.001	-0.050***	0.001	-0.006	0.005	-0.051***	0.002	-0.009
	(0.005)	(0.012)	(0.005)	(0.006)	(0.005)	(0.015)	(0.008)	(0.006)
Constant	0.232***	-0.086***	0.441***	0.214***	0.155***	-0.002	0.435***	0.157***
	(0.010)	(0.020)	(0.010)	(0.008)	(0.009)	(0.025)	(0.012)	(0.010)
Observations	17197	17175	17233	17236	16021	16019	16020	16023
R-squared	0.000	0.004	0.000	0.003	0.001	0.006	0.001	0.004

Standard errors are clustered on the running variable (high school rank). , *** 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	-0.021***	-0.008*	0.005	0.023***	0.014***	-0.048***	-0.009**	0.007	-0.001	0.014***
	(0.005)	(0.005)	(0.005)	(0.009)	(0.005)	(0.005)	(0.004)	(0.006)	(0.014)	(0.004)
Top 10% Rank Dummy	**0.178*** **	**0.023* **	**-0.001**	**-0.127*** **	**-0.044*** **	**0.038*** **	**-0.005**	**0.010**	**-0.108*** **	**-0.016**
	(0.012)	**(0.012)**	**(0.014)**	**(0.028)**	**(0.013)**	**(0.012)**	**(0.011)**	**(0.017)**	**(0.039)**	**(0.014)**
Interaction	0.018***	0.008	0.001	-0.068***	-0.012*	0.048***	0.007	0.001	-0.065***	-0.012**
	(0.005)	(0.005)	(0.006)	(0.011)	(0.006)	(0.005)	(0.005)	(0.008)	(0.017)	(0.006)
Constant	0.797***	0.207***	0.454***	0.058***	0.238***	0.961***	0.153***	0.440***	0.019	0.154***
	(0.011)	(0.010)	(0.012)	(0.021)	(0.009)	(0.012)	(0.008)	(0.013)	(0.031)	(0.010)
Observations	17236	15303	15338	15341	15341	16023	15087	15087	15088	15089
R-squared	0.130	0.002	0.001	0.004	0.008	0.106	0.001	0.001	0.005	0.005

Standard errors are clustered on the running variable (high school rank). , *** 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	-0.004	-0.009	0.002	0.034***	0.021***	0.003	-0.006	0.011	-0.006	0.013***
	(0.006)	(0.006)	(0.007)	(0.011)	(0.005)	(0.005)	(0.004)	(0.007)	(0.016)	(0.004)
Top 10% Rank Dummy	**-0.068*** **	**0.022**	**-0.008**	**-0.078* **	**-0.028* **	**0.021**	**0.012**	**0.011**	**-0.114** **	**-0.017**
	(0.016)	**(0.016)**	**(0.018)**	**(0.040)**	**(0.017)**	**(0.014)**	**(0.012)**	**(0.021)**	**(0.053)**	**(0.016)**
Interaction	-0.005	0.011	0.004	-0.067***	-0.016**	-0.002	0.009	-0.001	-0.071***	-0.016**
	(0.006)	(0.007)	(0.008)	(0.016)	(0.007)	(0.006)	(0.006)	(0.010)	(0.020)	(0.006)
Constant	0.683***	0.199***	0.465***	0.005	0.226***	0.625***	0.121***	0.434***	-0.056	0.139***
	(0.013)	(0.012)	(0.013)	(0.026)	(0.011)	(0.013)	(0.009)	(0.017)	(0.042)	(0.011)
Observations	15341	9950	9961	9961	9961	15089	9633	9634	9633	9634
R-squared	0.002	0.002	0.001	0.003	0.010	0.001	0.001	0.001	0.008	0.004
AIC	22690	18074	13891	1562	17756	22595	21596	13511	2696	20328
Stata AIC	20842	10159	14373	26702	10508	21433	5737	13825	24637	7008

Standard errors are clustered on the running variable (high school rank). , *** p<0.01, ** p<0.05, * p<0.1

Table 6
Discontinuities in College Performance Measures

	UT						A&M					
	(1) 1st GPA	(2) 4^{th} 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	(12) Rank of Major
Recentered Class Rank	-0.004	-0.005	0.018***	-0.010	-0.004	-0.288	-0.006	-0.007	0.005	0.003	-0.007*	-0.478***
	(0.011)	(0.008)	(0.006)	(0.009)	(0.004)	(0.221)	(0.012)	(0.007)	(0.005)	(0.005)	(0.004)	(0.145)
Top 10% Rank Dummy	**-0.014**	**-0.014**	**-0.031***	**-0.012**	**-0.019***	**-1.135****	**-0.002**	**0.010**	**0.010**	**0.053*****	**0.001**	**-0.111**
	(0.030)	**(0.023)**	**(0.017)**	**(0.029)**	**(0.011)**	**(0.515)**	**(0.040)**	**(0.022)**	**(0.014)**	**(0.014)**	**(0.011)**	**(0.474)**
Interaction	-0.040***	-0.027***	-0.023***	-0.007	-0.015***	-0.782***	-0.037**	-0.026***	-0.011**	-0.010*	-0.003	0.058
	(0.013)	(0.010)	(0.008)	(0.011)	(0.005)	(0.261)	(0.016)	(0.009)	(0.005)	(0.006)	(0.005)	(0.210)
Constant	2.987***	3.022***	0.716***	0.348***	2.896***	25.856***	2.705***	2.879***	0.872***	0.182***	2.864***	24.641***
	(0.024)	(0.017)	(0.013)	(0.021)	(0.009)	(0.418)	(0.032)	(0.018)	(0.012)	(0.011)	(0.007)	(0.307)
Observations	9934	7096	9922	6155	9934	9934	9632	8567	9629	8927	9632	9632
R-squared	0.005	0.006	0.005	0.003	0.006	0.008	0.007	0.011	0.001	0.006	0.006	0.007

Standard errors are clustered on the running variable (high school rank). , *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Tables

Table 1A

Descriptive Statistics Comparison of Full Sample and Analysis Sample (85-95% Ranked Student)

	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	17236	0.89	0.31	68397	0.73	0.45	16023	0.94	0.23
Enroll	73427	0.46	0.50	17236	0.58	0.49	68397	0.46	0.50	16023	0.60	0.49
Minority	73191	0.22	0.41	17197	0.23	0.42	68363	0.15	0.36	16021	0.15	0.35
SAT Score	73015	1182.64	163.34	17175	1178.21	154.80	68295	1136.38	150.52	16019	1143.03	138.57
Male	73378	0.48	0.50	17233	0.45	0.50	68376	0.50	0.50	16020	0.44	0.50
Feeder High School	73427	0.23	0.42	17236	0.21	0.40	68397	0.20	0.40	16023	0.15	0.36
Minority|Admit	53561	0.20	0.40	15303	0.22	0.41	49593	0.15	0.36	15087	0.15	0.35
Male|Admit	53701	0.47	0.50	15338	0.45	0.50	49609	0.48	0.50	15087	0.44	0.50
SAT Score|Admit	53722	1217.21	157.29	15341	1189.88	151.50	49602	1164.90	146.88	15088	1146.38	138.73
Feeder|Admit	53724	0.23	0.42	15341	0.22	0.41	49617	0.18	0.38	15089	0.15	0.36
Minority|Enroll	33447	0.19	0.40	9950	0.20	0.40	31252	0.12	0.33	9633	0.12	0.33
Male|Enroll	33494	0.48	0.50	9961	0.45	0.50	31259	0.48	0.50	9634	0.44	0.50
SAT Score|Enroll	33494	1203.62	151.75	9961	1185.45	148.81	31252	1152.35	139.81	9633	1136.08	132.20
Feeder|Enroll	33494	0.24	0.43	9961	0.22	0.41	31259	0.17	0.38	9634	0.14	0.35
First Semester GPA	32829	3.06	0.82	9934	3.03	0.78	31252	2.76	0.79	9632	2.75	0.73
Fourth Semester GPA	24158	3.08	0.59	7096	3.05	0.57	27580	2.94	0.56	8567	2.92	0.52
Fourth Semester Persistence	32781	0.74	0.44	9922	0.72	0.45	31241	0.88	0.32	9629	0.89	0.31
4-Year Graduation	27779	0.27	0.44	6155	0.35	0.48	38895	0.17	0.37	8927	0.22	0.42
GPA in Chosen Major	32829	2.92	0.28	9934	2.91	0.28	31252	2.86	0.28	9632	2.87	0.26
Rank of Chosen Major	32829	26.99	14.38	9934	26.36	14.40	31252	24.27	11.57	9632	24.72	11.17

Table 3A
Robustness Checks of Table 3 Results: Bandwidth Selection

	UT				TAMU			
Bandwidth	3	4	6	7	3	4	6	7
Minority								
Recentered GPA	-0.003	-0.003	-0.001	-0.001	-0.002	-0.003	-0.001	-0.001
	(0.006)	(0.004)	(0.002)	(0.002)	(0.006)	(0.003)	(0.002)	(0.002)
Top 10% Dummy	-0.009	-0.000	0.002	-0.003	-0.002	-0.000	0.005	0.004
	(0.014)	(0.013)	(0.010)	(0.009)	(0.013)	(0.010)	(0.009)	(0.009)
Interaction	-0.004	0.003	0.001	-0.002	-0.000	0.001	0.001	-0.001
	(0.008)	(0.005)	(0.003)	(0.002)	(0.007)	(0.003)	(0.003)	(0.002)
Constant	0.234***	0.234***	0.231***	0.230***	0.150***	0.149***	0.146***	0.145***
	(0.012)	(0.010)	(0.008)	(0.008)	(0.010)	(0.007)	(0.007)	(0.006)
Observations	12428	16706	25471	29824	11737	19362	23331	27209
Test Score								
Recentered GPA	-0.001	0.001	-0.014**	-0.013***	-0.013	-0.010	-0.020***	-0.019***
	(0.013)	(0.010)	(0.006)	(0.004)	(0.017)	(0.012)	(0.006)	(0.004)
Top 10% Dummy	0.023	0.004	-0.034	-0.040*	-0.055	-0.082**	-0.099***	-0.107***
	(0.031)	(0.028)	(0.023)	(0.021)	(0.039)	(0.035)	(0.028)	(0.026)
Interaction	-0.024	-0.046***	-0.038***	-0.042***	-0.027	-0.056***	-0.048***	-0.054***
	(0.019)	(0.012)	(0.007)	(0.006)	(0.022)	(0.015)	(0.007)	(0.006)
Constant	-0.079***	-0.082***	-0.056***	-0.059***	-0.006	-0.008	0.006	0.004
	(0.023)	(0.020)	(0.016)	(0.014)	(0.030)	(0.025)	(0.020)	(0.019)
Observations	12412	16683	25443	29788	11736	15578	23331	27211
Male								
Recentered GPA	0.003	0.005	0.004	0.007**	0.005	0.008	0.011***	0.010***
	(0.009)	(0.004)	(0.004)	(0.003)	(0.007)	(0.006)	(0.003)	(0.002)
Top 10% Dummy	0.010	0.011	0.009	0.017	0.019	0.015	0.019	0.011
	(0.015)	(0.013)	(0.012)	(0.011)	(0.019)	(0.017)	(0.013)	(0.012)
Interaction	0.004	-0.001	0.001	-0.000	0.009	-0.001	-0.004	-0.006*
	(0.010)	(0.006)	(0.004)	(0.003)	(0.011)	(0.008)	(0.004)	(0.003)
Constant	0.444***	0.441***	0.443***	0.438***	0.436***	0.433***	0.428***	0.431***
	(0.013)	(0.010)	(0.010)	(0.008)	(0.014)	(0.012)	(0.010)	(0.009)
Observations	12456	16740	25520	29879	11737	15579	23331	27211
Feeder								
Recentered GPA	0.007	0.007*	0.006**	0.006***	0.016**	0.011**	0.006**	0.006**
	(0.005)	(0.004)	(0.002)	(0.002)	(0.006)	(0.005)	(0.003)	(0.003)
Top 10% Dummy	-0.025*	-0.026**	-0.022**	-0.018*	-0.006	-0.019	-0.020*	-0.016
	(0.014)	(0.013)	(0.010)	(0.010)	(0.017)	(0.015)	(0.012)	(0.012)
Interaction	-0.006	-0.007	-0.002	-0.001	-0.007	-0.011*	-0.000	0.000
	(0.009)	(0.006)	(0.003)	(0.002)	(0.009)	(0.007)	(0.003)	(0.003)
Constant	0.216***	0.216***	0.218***	0.217***	0.151***	0.156***	0.165***	0.163***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.011)	(0.011)	(0.009)	(0.009)
Observations	12458	16743	25527	29889	11738	15582	23336	27216

Table 4A:
Robustness Checks of Table 4 Results: Bandwidth Selection

	UT				TAMU			
Bandwidth	3	4	6	7	3	4	6	7
Minority								
Recentered GPA	-0.009	-0.009*	-0.005**	-0.004*	-0.005	-0.010***	-0.004	-0.002
	(0.005)	(0.005)	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.002)
Top 10% Dummy	0.017	0.023*	0.027***	0.024***	-0.002	-0.008	0.006	0.006
	(0.013)	(0.012)	(0.010)	(0.009)	(0.013)	(0.011)	(0.009)	(0.009)
Interaction	0.004	0.010*	0.004	0.001	0.003	0.008*	0.003	0.000
	(0.007)	(0.006)	(0.003)	(0.002)	(0.007)	(0.005)	(0.003)	(0.002)
Constant	0.209***	0.209***	0.203***	0.200***	0.150***	0.156***	0.145***	0.143***
	(0.010)	(0.010)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.006)
Observations	11072	14863	22659	26547	11151	14689	21780	25331
Test Score								
Recentered GPA	0.018	0.021**	0.007	0.006	0.011	0.005	-0.009	-0.011**
	(0.015)	(0.009)	(0.006)	(0.005)	(0.021)	(0.013)	(0.007)	(0.005)
Top 10% Dummy	-0.111***	-0.129***	-0.166***	-0.175***	-0.067	-0.101**	-0.123***	-0.137***
	(0.033)	(0.029)	(0.025)	(0.022)	(0.043)	(0.039)	(0.032)	(0.029)
Interaction	-0.043**	-0.065***	-0.058***	-0.061***	-0.051**	-0.072***	-0.059***	-0.063***
	(0.020)	(0.012)	(0.008)	(0.006)	(0.025)	(0.017)	(0.009)	(0.007)
Constant	0.063**	0.060***	0.084***	0.085***	0.005	0.011	0.031	0.034
	(0.025)	(0.021)	(0.018)	(0.016)	(0.036)	(0.030)	(0.025)	(0.023)
Male								
Recentered GPA	0.006	0.005	0.007	0.009***	0.011	0.009	0.012***	0.010***
	(0.012)	(0.006)	(0.004)	(0.003)	(0.008)	(0.006)	(0.003)	(0.002)
Top 10% Dummy	0.001	-0.003	-0.001	0.007	0.021	0.011	0.016	0.006
	(0.018)	(0.015)	(0.013)	(0.012)	(0.019)	(0.017)	(0.013)	(0.013)
Interaction	0.001	-0.000	-0.001	-0.003	0.002	-0.002	-0.005	-0.006*
	(0.013)	(0.007)	(0.004)	(0.003)	(0.011)	(0.009)	(0.004)	(0.003)
Constant	0.453***	0.455***	0.453***	0.447***	0.434***	0.437***	0.432***	0.436***
	(0.016)	(0.012)	(0.011)	(0.010)	(0.015)	(0.013)	(0.010)	(0.009)
Feeder								
Recentered GPA	0.017**	0.014***	0.010***	0.012***	0.021***	0.015***	0.008***	0.008***
	(0.007)	(0.005)	(0.003)	(0.002)	(0.007)	(0.005)	(0.003)	(0.003)
Top 10% Dummy	-0.041***	-0.047***	-0.047***	-0.040***	-0.003	-0.016	-0.018	-0.016
	(0.015)	(0.014)	(0.011)	(0.011)	(0.016)	(0.014)	(0.012)	(0.011)
Interaction	-0.015	-0.014**	-0.006*	-0.007**	-0.012	-0.015**	-0.003	-0.002
	(0.010)	(0.007)	(0.003)	(0.003)	(0.009)	(0.006)	(0.004)	(0.003)
Constant	0.235***	0.239***	0.245***	0.241***	0.147***	0.153***	0.163***	0.163***
	(0.010)	(0.010)	(0.008)	(0.008)	(0.011)	(0.010)	(0.009)	(0.009)
Admit								
Recentered GPA	-0.024***	-0.022***	-0.021***	-0.019***	-0.064***	-0.048***	-0.034***	-0.029***
	(0.008)	(0.005)	(0.003)	(0.002)	(0.006)	(0.005)	(0.003)	(0.003)
Top 10% Dummy	0.173***	0.176***	0.179***	0.186***	0.020	0.038***	0.060***	0.070***
	(0.014)	(0.012)	(0.009)	(0.008)	(0.013)	(0.012)	(0.011)	(0.011)
Interaction	0.020**	0.019***	0.019***	0.017***	0.064***	0.048***	0.034***	0.029***
	(0.008)	(0.005)	(0.003)	(0.002)	(0.006)	(0.005)	(0.003)	(0.003)
Constant	0.801***	0.799***	0.798***	0.793***	0.979***	0.961***	0.939***	0.929***
	(0.014)	(0.012)	(0.009)	(0.008)	(0.013)	(0.012)	(0.011)	(0.011)

Table 5A
Robustness Checks of Table 5 Results: Bandwidth Selection

	UT				TAMU			
Bandwidth	3	4	6	7	3	4	6	7
Minority								
Recentered GPA	-0.005	-0.010	-0.008***	-0.007***	-0.006	-0.008**	-0.001	-0.000
	(0.007)	(0.006)	(0.003)	(0.002)	(0.006)	(0.004)	(0.003)	(0.002)
Top 10% Dummy	0.024	0.024	0.018	0.019	0.007	0.007	0.020*	0.018*
	(0.017)	(0.016)	(0.013)	(0.012)	(0.013)	(0.012)	(0.011)	(0.010)
Interaction	0.005	0.013*	0.005	0.003	0.005	0.009*	0.004	0.001
	(0.010)	(0.008)	(0.004)	(0.003)	(0.008)	(0.005)	(0.004)	(0.003)
Constant	0.195***	0.200***	0.196***	0.194***	0.121***	0.124***	0.114***	0.112***
	(0.013)	(0.013)	(0.010)	(0.009)	(0.010)	(0.009)	(0.008)	(0.007)
Observations	7193	9663	14764	17225	7112	9385	13979	16162
Test Score								
Recentered GPA	0.023	0.031***	0.017**	0.013**	0.012	-0.000	-0.013	-0.015**
	(0.014)	(0.011)	(0.007)	(0.006)	(0.028)	(0.016)	(0.009)	(0.007)
Top 10% Dummy	-0.055	-0.083**	-0.118***	-0.134***	-0.055	-0.106**	-0.122***	-0.121***
	(0.043)	(0.040)	(0.033)	(0.030)	(0.061)	(0.053)	(0.043)	(0.039)
Interaction	-0.026	-0.064***	-0.055***	-0.055***	-0.053	-0.076***	-0.062***	-0.058***
	(0.023)	(0.017)	(0.009)	(0.007)	(0.033)	(0.021)	(0.011)	(0.009)
Constant	0.016	0.010	0.033	0.041**	-0.076	-0.063	-0.043	-0.040
	(0.027)	(0.026)	(0.021)	(0.020)	(0.050)	(0.042)	(0.034)	(0.031)
Male								
Recentered GPA	-0.001	-0.001	0.004	0.009***	0.022**	0.012	0.013***	0.011***
	(0.010)	(0.006)	(0.004)	(0.003)	(0.009)	(0.008)	(0.004)	(0.003)
Top 10% Dummy	-0.014	-0.017	-0.010	0.003	0.031	0.010	0.011	-0.001
	(0.020)	(0.018)	(0.016)	(0.015)	(0.023)	(0.021)	(0.016)	(0.015)
Interaction	0.007	0.004	0.001	-0.003	-0.005	-0.005	-0.005	-0.006
	(0.013)	(0.008)	(0.005)	(0.004)	(0.012)	(0.010)	(0.005)	(0.004)
Constant	0.469***	0.469***	0.464***	0.454***	0.422***	0.432***	0.431***	0.435***
	(0.014)	(0.012)	(0.011)	(0.011)	(0.018)	(0.017)	(0.013)	(0.012)
Feeder								
Recentered GPA	0.022***	0.020***	0.012***	0.014***	0.025***	0.014***	0.009***	0.009***
	(0.008)	(0.005)	(0.003)	(0.003)	(0.007)	(0.005)	(0.003)	(0.003)
Top 10% Dummy	-0.030	-0.031*	-0.039***	-0.034**	0.005	-0.017	-0.014	-0.008
	(0.019)	(0.017)	(0.014)	(0.013)	(0.018)	(0.016)	(0.014)	(0.013)
Interaction	-0.020*	-0.016**	-0.004	-0.005	-0.017*	-0.017**	-0.006	-0.002
	(0.012)	(0.007)	(0.004)	(0.003)	(0.010)	(0.007)	(0.004)	(0.003)
Constant	0.225***	0.228***	0.242***	0.238***	0.128***	0.138***	0.145***	0.146***
	(0.013)	(0.012)	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)	(0.010)
Enroll								
Recentered GPA	-0.016**	-0.016***	-0.012***	-0.012***	-0.042***	-0.028***	-0.016***	-0.015***
	(0.007)	(0.004)	(0.003)	(0.002)	(0.009)	(0.007)	(0.005)	(0.003)
Top 10% Dummy	0.049***	0.057***	0.073***	0.083***	0.028	0.042**	0.061***	0.072***
	(0.014)	(0.014)	(0.013)	(0.012)	(0.020)	(0.019)	(0.017)	(0.015)
Interaction	-0.001	0.006	0.008**	0.011***	0.042***	0.028***	0.016***	0.019***
	(0.008)	(0.005)	(0.004)	(0.003)	(0.010)	(0.008)	(0.005)	(0.004)
Constant	0.544***	0.545***	0.539***	0.538***	0.616***	0.601***	0.582***	0.580***
	(0.011)	(0.010)	(0.009)	(0.008)	(0.019)	(0.018)	(0.015)	(0.014)

Table 6A
Robustness Checks of Table 6 Results: Bandwidth Selection

	UT				TAMU			
Bandwidth	3	4	6	7	3	4	6	7
1st GPA								
Recentered GPA	0.004	-0.008	-0.021***	-0.020***	-0.001	-0.010	-0.020***	-0.017***
	(0.013)	(0.011)	(0.006)	(0.005)	(0.020)	(0.013)	(0.007)	(0.006)
Top 10% Dummy	-0.020	-0.021	-0.039	-0.049**	0.003	-0.012	-0.033	-0.031
	(0.031)	(0.030)	(0.025)	(0.024)	(0.048)	(0.040)	(0.032)	(0.028)
Interaction	-0.060***	-0.037***	-0.022***	-0.027***	-0.041	-0.039**	-0.032***	-0.036***
	(0.017)	(0.013)	(0.007)	(0.006)	(0.025)	(0.016)	(0.009)	(0.007)
Constant	2.978***	2.992***	3.015***	3.013***	2.700***	2.709***	2.723***	2.718***
	(0.025)	(0.024)	(0.020)	(0.019)	(0.038)	(0.033)	(0.026)	(0.023)
Observations	7181	9646	14730	17181	7110	9384	13979	16163
4th GPA								
Recentered GPA	0.004	-0.008	-0.010**	-0.009**	-0.004	-0.008	-0.012***	-0.015***
	(0.013)	(0.008)	(0.005)	(0.004)	(0.011)	(0.007)	(0.004)	(0.003)
Top 10% Dummy	0.002	-0.015	-0.028	-0.039**	0.007	0.004	-0.004	-0.014
	(0.025)	(0.023)	(0.020)	(0.019)	(0.025)	(0.022)	(0.018)	(0.016)
Interaction	-0.031*	-0.023**	-0.026***	-0.033***	-0.033**	-0.029***	-0.026***	-0.025***
	(0.017)	(0.011)	(0.006)	(0.005)	(0.014)	(0.009)	(0.005)	(0.004)
Constant	3.012***	3.026***	3.031***	3.029***	2.876***	2.880***	2.885***	2.891***
	(0.018)	(0.017)	(0.015)	(0.014)	6299	8346	12483	14453
Observations	5095	6871	10506	12284	6383	8460	12657	14649
4th Persist								
Recentered GPA	0.016**	0.017**	0.012***	0.010***	0.002	0.005	-0.003	-0.002
	(0.007)	(0.006)	(0.003)	(0.003)	(0.008)	(0.005)	(0.003)	(0.002)
Top 10% Dummy	-0.033*	-0.030*	-0.032**	-0.042***	0.007	0.009	-0.006	0.000
	(0.018)	(0.017)	(0.014)	(0.013)	(0.016)	(0.014)	(0.012)	(0.011)
Interaction	-0.019**	-0.019**	-0.012***	-0.012***	-0.008	-0.012**	-0.005	-0.004
	(0.010)	(0.008)	(0.004)	(0.004)	(0.009)	(0.006)	(0.004)	(0.003)
Constant	0.720***	0.718***	0.725***	0.730***	0.875***	0.872***	0.885***	0.882***
	(0.013)	(0.013)	(0.011)	(0.010)	(0.014)	(0.013)	(0.011)	(0.010)
Observations	7172	9634	14712	17158	7107	9381	13976	16159
4th Grad								
Recentered GPA	-0.006	-0.007	-0.009*	-0.005	-0.003	0.001	-0.004	-0.006***
	(0.016)	(0.009)	(0.005)	(0.004)	(0.007)	(0.005)	(0.003)	(0.002)
Top 10% Dummy	-0.009	-0.004	0.011	0.020	0.042***	0.051***	0.038***	0.043***
	(0.034)	(0.029)	(0.024)	(0.022)	(0.015)	(0.014)	(0.013)	(0.012)
Interaction	-0.013	-0.006	0.006	0.004	-0.008	-0.009	-0.007*	0.000
	(0.019)	(0.011)	(0.007)	(0.005)	(0.010)	(0.006)	(0.004)	(0.003)
Constant	0.343***	0.344***	0.346***	0.340***	0.188***	0.184***	0.192***	0.197***
	(0.026)	(0.021)	(0.017)	(0.015)	(0.012)	(0.011)	(0.009)	(0.009)
Observations	4443	5961	9149	10790	6532	8675	13046	15318
Major GPA								
Recentered GPA	-0.008	-0.006	-0.003	-0.003	-0.012**	-0.005	-0.007***	-0.007***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)
Top 10% Dummy	-0.027**	-0.020*	-0.018**	-0.017**	-0.002	0.003	0.004	0.001
	(0.013)	(0.011)	(0.009)	(0.008)	(0.013)	(0.011)	(0.009)	(0.008)

Interaction	-0.013*	-0.012**	-0.014***	-0.014***	0.004	-0.006	-0.002	-0.003
	(0.007)	(0.005)	(0.003)	(0.002)	(0.008)	(0.005)	(0.002)	(0.002)
Constant	2.901***	2.898***	2.896***	2.895***	2.869***	2.861***	2.864***	2.864***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.006)
Observations	7181	9646	14730	17181	7110	9384	13979	16163
Major Rank								
Recentered GPA	-0.607*	-0.379*	-0.272**	-0.198**	-0.467**	-0.395***	-0.334***	-0.320***
	(0.314)	(0.226)	(0.104)	(0.089)	(0.215)	(0.133)	(0.073)	(0.064)
Top 10% Dummy	-1.605***	-1.191**	-0.921**	-0.729*	-0.089	-0.034	0.225	0.084
	(0.580)	(0.519)	(0.410)	(0.395)	(0.559)	(0.473)	(0.378)	(0.355)
Interaction	-0.538	-0.646**	-0.621***	-0.673***	0.067	-0.047	-0.019	-0.115
	(0.354)	(0.268)	(0.127)	(0.105)	(0.345)	(0.211)	(0.107)	(0.087)
Constant	26.230***	25.973***	25.900***	25.749***	24.609***	24.536***	24.410***	24.379***
	(0.479)	(0.419)	(0.331)	(0.326)	(0.341)	(0.295)	(0.244)	(0.239)
Observations	7181	9646	14730	17181	7110	9384	13979	16163