Do Public Universities Practice Gender Sensitive Admissions?

Dylan Conger
George Washington University
805 21st Street NW
Room 601G
Washington, DC 20052
dconger@gwu.edu
202-994-1456

Lisa Dickson
University of Maryland Baltimore County
1000 Hilltop Circle
Baltimore, MD 21250
ldickson@umbc.edu
410-455-2176

May 2011

We are grateful to the Texas Higher Education Opportunity Project, and Marta Tienda in particular, for maintaining these comprehensive records on Texas college applicants and making them available to us for analysis. We also thank Burt Barnow, Stephanie Riegg Cellini, Kalena Cortes, Erin Dunlap, Doug Lamdin, Brett Wendling and participants at the Association for Education Finance and Policy, Association for Public Policy Analysis and Management, American University Department of Public Administration and Policy seminar, and University of Maryland Baltimore County Economics seminar for very helpful comments. Megan Hatch provided excellent research assistance. We are responsible for any errors or omissions.

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Abstract

We use the passage of the 1998 Top 10 percent policy in Texas as a natural experiment to test whether males receive preferential treatment in college admissions at the state's two flagship public universities. The policy requires public universities in Texas to admit in-state students who graduate in the top decile of their high school class, and these students are disproportionately female. We examine whether the difference in the number of women and men who are automatically-admitted under the top 10 policy increases the probability that males in the top 10 *in*eligible applicant pool are admitted. We find evidence of such preferences at one of the two institutions.

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An estimated 57 percent of enrollees in U.S. degree-granting postsecondary institutions are women, and the National Center on Education projects an enrollment increase of 21 percent for women relative to only 12 percent for men through 2019 (William J. Hussar and Tabitha M. Bailey 2011). Much of the gender imbalance on college campuses appears to be driven by women's higher high school grades, high school graduation rates, and likelihood of applying to college (Brian Jacob 2002). Several college administrators have expressed concern over the imbalance to journalists and court officials because they fear that unequal gender ratios in enrollments reduce applications from top male and female high school graduates (John Tierney 2006). Some private universities have also reported that they employ strategies to increase the male share of applicants and weight male and female applicants differently in the admissions process (Jennifer Delahunty Britz 2006; Nancy Gibbs 2008; Tamar Lewin 2006).[1] These reports have led to charges in the popular press that many universities are practicing "affirmative action for boys", which would imply that they accept less qualified men in order to lower the ratio of women to men in their entering classes (Jose Cardenas 2007; Nancy Gibbs 2008; John Tierney 2006).

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[1] For instance, the Dean of Admissions and Financial Aid at Kenyon College in Ohio wrote an op-ed piece in the *Washington Post* entitled "To All the Girls I've Rejected", where she reported that her university often admitted less-qualified male applicants in an effort to maintain gender balance (Jennifer Delahunty Britz 2006). In a *New York Times* article, journalist Tamar Lewin interviews the Vice President of Enrollment at Dickinson College in Pennsylvania, who reports that they sometimes give preference to males in admissions (Tamar Lewin 2006).

Several federal and state statutes govern the legality of such practices. Most relevant is Title IX of the 1972 Education Amendments, which prohibits sex discrimination in educational institutions that receive federal monies. To date, there has been one lawsuit filed concerning gender sensitive admissions; in 2000, a case was brought against the University of Georgia for awarding additional points to minorities and males in the admissions process. The district court ruled against the university and the defendants chose not to appeal the decision regarding their use of gender in admissions, so gender-based affirmative action has not yet reached higher courts (see *Johnson I*, 106 F. Supp. 2nd at 1363).[2] In 2009, the U.S. Civil Rights Commission launched an investigation of gender sensitive admissions practices by requesting applications and admissions records from a sample of 19 public and private universities in the Washington DC metropolitan area. In March of 2011, the Commission voted to end the investigation due to the limited and poor quality of the data obtained from the subpoena (Nancy Greisemer 2011; Ilana Kowarski 2010).

In the meantime, the research community has produced only one study on the use of gender sensitive admissions policies. Using data on 13 private liberal arts colleges, Sandy Baum and Eban Goodstein (2005) find higher rates of admission among males who apply to colleges with higher shares of female applicants, particularly in historically female-only colleges. No other studies have examined the practice. This omission from the research literature is partially driven by the relative newness of the issue, but also by the empirical challenges in isolating evidence that demographic characteristics play a role in admissions decisions. Few universities share data on their applicant pools, and even when made available to researchers, the data do not contain quantifiable measures of all applicant characteristics that inform admissions decisions.

[2] See Debra Franzese (2007) for one legal analysis of the constitutionality of gender sensitive admissions practices.

In this study, we address this identification challenge with data on applicants to the two most selective universities in Texas, where a state policy was enacted that inadvertently required universities to admit more female than male students. The Texas Top 10 percent plan, passed into law in 1997 and implemented in 1998, requires public universities to admit in-state students who graduate in the top 10 percent of their high school class. Given female's higher high school grades, this policy forced universities to automatically admit more females than males. The plan was designed to address racial imbalance in applications and enrollments (and not gender imbalance), thus we use the plausibly exogenous shock to the gender ratio of automatically-accepted students to examine the effects of gender on admissions decisions for students not automatically admitted under the policy. In short, we identify the effect of gender in admissions decisions regarding top 10 *in*eligible applicants off of increases in the number of top 10 eligible females that universities were required to admit. Our identifying assumption is that these deviations in the number of automatically-admitted females are orthogonal to unobserved differences in the characteristics of top 10 ineligible male and female applicants.

With pre and post top 10 data on applicants to the two public flagships in the state, the focus of our specification is a three-way interaction term between whether the applicant is male, whether the application was submitted in a top 10 year, and the gender imbalance in the number of automatically-admitted students. We also estimate a number of sensitivity analyses and examine variation in gender preferences by applicants' racial/ethnic background. Our main results, which hold under robustness checks, provide no evidence of male preferences at the University of Texas (UT) at Austin, and evidence of male preferences at Texas A&M at College Station. At Texas A&M, the models also suggest that the preference given to males was greatest among black applicants and nonexistent among Asian applicants. Both institutions faced similar constraints (large numbers of top 10 applicants and automatically-admitted females), thus we speculate in the discussion that the military and agricultural history of Texas A&M may have led to an infrastructure that requires a certain number of male freshman.

The paper is organized into 4 additional sections. Section I describes the prior research and policy on affirmative action in college admissions as well as our identification strategy and estimating equations. Section II describes the data, provides descriptive information on the applicants, and offers a falsification test for our identifying equation. Section III presents the main results, sensitivity and heterogeneity analyses, and a discussion. Section IV concludes.

I. Background and Identification Strategy

A. Public Policy and Research on Affirmative Action in College Admissions

Though the literature on gender-based affirmative action in higher education is slim, there is a large literature on the use of race in college admissions. In one of the first such analyses, Thomas J. Kane (1998) finds that black and Hispanic applicants are approximately 8 to 10 percentage-points more likely to be admitted to selective colleges than white applicants with the same observable qualifications. Recent legislative and judicial decisions prohibiting the use of race in college admissions in several states have created quasi-experimental conditions for further investigations into the effects of race on college admissions as well as the effect of bans on college diversity. Most relevant to our inquiry, the *Hopwood v. University of Texas* decision in 1996 banned the practice of affirmative action for minority students in all Texas public post-secondary institutions. Mark C. Long and Marta Tienda (2008) examine application records from several Texas institutions and find evidence of affirmative action at selective universities prior to the ban as well as evidence that college administrators placed greater value on applicant characteristics that favored minority applicants after the ban, such as home language and neighborhood poverty. See also David Card and Alan B. Krueger (2005), Lisa Dickson (2006a), Peter Hinrichs (forthcoming), and Mark C. Long (2004a; 2004b) for other analyses of the effect of affirmative action bans on minority students' college-going behavior and admissions.

In partial response to race-based affirmative action bans, several states have also passed x percentage plans (namely, California's 4 percent plan, Texas's 10 percent plan, and Florida's Talented 20 program), which guarantee admission to a public university for students who graduate in the top x percent of their high school class. The Texas legislature passed H.B. 588, which mandates public universities (beginning with the fall admission cohort of 1998) to admit students who graduate in the top 10 percent of a Texas high school. By basing admissions decisions on high school class rank, x percent policies provide a means for colleges and universities to admit minority applicants without explicitly using race in admissions.

Several studies have evaluated the impact of the top 10 percent rule on racial disparities in applications (Rodney Andrews, Vimal Ranchod, and Viji Sathy 2010; Angel Harris and Marta Tienda 2010; Mark C. Long and Marta Tienda 2010) and enrollments (Lisa Dickson 2006b; Angel Harris and Marta Tienda 2010; Mark C. Long and Marta Tienda 2008; Sunny Niu and Marta Tienda 2010). In contrast, there have been no inquiries about the effects of the policy on the gender composition of the applicant and admissions pools, despite reasons to expect such effects. To elaborate, it is well-documented that while females earn either equal or lower scores on college entrance exams, they typically earn much higher high school grades than males, both nationally and in Texas (Dylan Conger and Mark C. Long 2010; Brian Jacob 2002). Thus, the top x percent plans, which require universities to admit students at the top of their graduating classes irrespective of their test scores, may force universities to admit higher shares of females than they might have admitted if no such requirement existed.

In Texas, the two flagship public institutions—Texas A&M and UT Austin—have been particularly impacted by H.B. 588. In recent years, the universities have experienced substantial growth in the number of students who are automatically-admitted under H.B. 588, most notably at UT Austin where an estimated 81 percent of entering freshman from Texas high schools in 2008 were H.B. 588 automatic admits (The University of Texas at Austin, 2008).[3] In Section II below, we demonstrate that a large, and increasing, share of these automatically-admitted students are female.

B. Identification Strategy and Estimating Equations

We use this exogenous shock to the gender ratio of automatically-admitted students to uncover signs of gender-sensitivity in admissions decisions among applicants who are ineligible for the top 10 policy. We offer two assumptions. First, if increasing female shares of automatically-admitted students raise concerns about gender imbalance in enrollments, we expect admissions officers to respond by giving preference to males who do not qualify for automatic admission. Second, we assume that these increases in the female share of automatically-admitted students are uncorrelated with unobserved applicant characteristics (e.g., teacher recommendation letters, extracurricular activities) that might explain differential probabilities of admission for male and female top 10 ineligible applicants. We provide a partial test of the second assumption in Section II.

Our main specification is as follows:

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[3] In response to complaints from university presidents and the public, the legislature amended the policy in 2009. One amendment to the law permits UT Austin to accept students with the highest class ranks until it hits 75% of the entering freshman class.

$$(1)\ Admit_{ijt} = \beta_0 + \beta_1(Male_i\ x\ Imb_t\ x\ TopTen_t) + \ \beta_2(Male_i\ x\ Imb_t)$$
$$+ \beta_3(Male_i\ x\ TopTen_t)$$
$$+ \beta_4(Imb_t\ x\ TopTen_t) + \beta_5 Male_i + \ \beta_6 Imb_t + \beta_7 TopTen_i + \ \beta_8 X_i \ + a_j + \ \epsilon_{ijt}$$

where $Admit_{ijt}$ equals 1 if applicant *i* from high school *j* whose year of desired admission *t* is admitted to the university. $Male_i$ is an indicator set to 1 if the student is male; Imb_t is equal to the imbalance in the gender of top 10 applicants (specifically, the number of top 10 eligible females minus the number of top 10 eligible males in 100s) in the admission year; $TopTen_t$ is equal to 1 if the applicant applied after 1997; X_i is a vector of student academic and demographic characteristics, including highest combined SAT or ACT score (converted to the SAT scale),[4] high school class rank (where 1 indicates the student is in the top 1 percent of her class), and race/ethnicity; and a_j are high school fixed effects. Regressions are estimated separately for each university; hence, we omit institution-level variables from all equations.

The coefficient of primary interest is $\beta_{1,}$ which provides an estimate of the differential effect of more female automatic admits on the probability of admission for non-automatic admits by gender after versus before the top 10 policy. If universities are tipping the scales to favor men in years when the automatically-admitted female population increases, then we would expect the estimated β_1 to be positive and significant. Linear combinations of several other parameter estimates are also of interest and interpreted in the results section below.

The inclusion of the students' academic qualifications, demographic characteristics, and high schools should mitigate biases due to omitted variables. Any remaining biases on the three-

[4] Following Mark Long and Marta Tienda (2008), we combine students' verbal and math scores on the SAT and ACT exams. For students who only took the ACT, we then convert their scores to the SAT scale using a conversation table provided by the College Board (Neil Dorans 2002).

way interaction term in Equation (1) could be driven by unobservables that render gender differences in the quality of applicants in post-top 10 years when there is an increase in the female share of the applicant pool different than previous years. We can think of no obvious candidates that would bias the results.

Equation (1) is estimated using linear probability models and all standard errors are Huber-White adjusted for clustering at the level of the year of desired admission. We test for the sensitivity of our choices with alternate specifications and examine variation in gender preferences by students' race/ethnicity.

II. Data, Descriptive Statistics, and Falsification Tests

The Texas Higher Education Opportunity Project[5] supplied us with approximately 10 years of applicant data from the two most selective public universities: Texas A&M and UT Austin. We use data on all top 10 eligible applicants to generate aggregate numbers of females and males in the top 10 eligible pool, then we restrict the estimating sample to the 195,201 applicants who were ineligible for the top 10 policy and who had complete data on all variables in Equation (1).

Table 1 provides summary statistics on enrollments and applications to both universities in the years before and after the top 10 policy. After top 10, both universities experienced increases (approximately two to three thousand) in the average number of applicants. This

[5] The Texas Higher Education Opportunity Project is a multi-year study directed by Marta Tienda (Princeton University) and her collaborators to study the college planning and enrollment behavior of students in Texas. More information on the study and access to the administrative data can be found at http://www.texastop10.princeton.edu.

growth was partially driven by increases in the college-eligible population (due to fertility and migration) in Texas (Marta Tienda and Teresa Sullivan 2009). However, at UT Austin, the increases were also driven by more applications from students eligible for automatic admission under top 10 (from 36.7 to 39.8 percent), while at Texas A&M, the rank-eligible share of applicants actually decreased (from 36.8 to 36.1 percent). Mark C. Long and Marta Tienda (2010) document a similar trend and provide a straightforward explanation: the top 10 law removed admissions uncertainties for rank-eligible students, which likely reduced their probability of applying to both universities. The results suggest that UT Austin served as the top choice for a larger number of rank-eligible applicants.[6] As a consequence of the increasing applicant pool, both universities lowered their admissions rates by approximately 3 percentage-points.

(Table 1 here)

The next three rows of the table focus on the gender composition of students at each university. In the years prior to the top 10 policy, the admitted students who enrolled were slightly less likely to be female (49.3% male at Texas A&M and 48.4% male at UT Austin). Yet, consistent with trends across the nation, the enrolled population became disproportionately female in the years after top 10 was enacted. This increase in female enrollments was driven by higher shares of female applicants overall, but also by the high share of females in the top 10

[6] Note that, in recent years, the universities have reported that their applications are saturated by top 10 applicants, yet our data show only up to 40% of applicants are rank-eligible. One explanation is that our data track applications for 4 to 5 years after the top 10 policy (up to 2003), yet surveys of high school graduates from Texas reveal that rank-eligible students from low-income and language minority families were not aware of the policy and may not have applied in these early years (Sunny Xinchun Niu, Teresa Sullivan, and Marta Tienda 2008).

applicant pool. At both universities, the female share of top 10 eligible applicants increased from approximately 55% before the policy to 58% after the policy.[7]

The second to last row of Table 1 translates these percentages into numbers of students. Before top 10, Texas A&M received, in an average year, applications from 490 more females than males in the top 10% of their class, while after the policy, they received applications from an average of 810 more females than males. UT Austin experienced an even larger increase in top female applicants after 1997. We refer to the numbers in the last column from here forward as the “imbalance" in the top 10 applicant pool. Our identification strategy relies on the variation in the imbalance across the years observed; at Texas A&M, the imbalance ranged from 210 to 610 females before the top 10 policy and from 630 to 1,020 females after the top 10 policy. At UT Austin, the respective minimum and maximum values are 190 to 610 before the policy and 710 to 1,170 after the policy. Though these numbers represent small shares of the total number of admitted students, we posit that the increases are large enough to affect gender imbalances in enrollment (and potentially influence admissions decisions), and that the variation in the imbalance is wide enough to generate precise estimates.

Table 2 provides the characteristics of the males and females in the top 10 ineligible applicant pool at both institutions. The “all” columns for both universities reveal that they draw from slightly different applicant pools; though the test scores and high school ranks of applicants to the two institutions tend to be similar, Texas A&M attracts fewer minority applicants, partially

[7] The female share of students ineligible for the top 10 plan also increased in these years; however, the increases were smaller than the increases among the top 10 candidates (the average share female among the top 10 ineligible applicants increased from 45 to 46 percent at Texas A&M and from 46 to 47 percent at UT Austin pre/post Texas top 10).

due to its location in a non-metropolitan region (College Station) of the state. At both institutions, however, males comprise a larger share of the rank-ineligible pool (approximately 55% at Texas A&M and 53% at UT Austin). Male rank-ineligible applicants also tend to have slightly lower class ranks than females. But on SAT/ACT scores and racial/ethnic background, the males and females who are ineligible for automatic admission under the top 10 policy are similar.

(Table 2 here)

The main assumption of our model is that small increases in the number of women who are automatically admitted under the policy are uncorrelated with unobserved and admissions-relevant characteristics of the male and female applicants in the top 10 ineligible applicant pool. A threat to our identification strategy would arise if rank-ineligible males became more or less positively selected as the female share in the automatically-admitted pool increased. To partially test this assumption, we examine the correlation between the imbalance in the gender composition of top 10 applicants and the observed characteristics of rank-ineligible females and males pre and post top 10. Table 3 provides the estimated coefficients on the interaction of the male, gender imbalance, and top 10 year variable from regressions of each student characteristic on all variables in Equation (1) except the student-level controls (X_i) and the high school fixed effects (a_j) – that is, the equation used here includes only the male, gender imbalance, and top ten year variables along with all possible interaction terms from these 3 variables.

(Table 3 here)

The results in Table 3 suggest that, of the 10 coefficients, only 1 is statistically significant at conventional levels. At Texas A&M, the high school rank of the male applicants in the rank-ineligible applicant pool increased by about 0.3 of a percentage-point in the years that the gender imbalance in the number of females in the rank-eligible applicant pool increased by 100. The lack of correlations on most variables and the small correlation on the rank variable for Texas A&M provide support for our assumption. Yet the difference on the rank variable may reflect real differences in the population of male and female applicants and are suggestive of additional differences that we have not observed. We consider this possibility in our discussion below.

III. Regression Results

A. Main and Alternative Specifications

Table 4 provides results from Equation (1) for both universities. Specification (1) provides the results of the main terms of interest, excluding student-level controls and high school fixed effects, while Specification (2) adds these covariates. We have ordered the results in a way that allows us to provide meaningful interpretations of the key estimated parameters, noting that the main coefficient of interest is on the 3-way interaction term. First, looking at Specification (1) for both schools, the near-zero and statistically insignificant coefficient on the gender imbalance indicates that a 100-female increase in the gender imbalance has no effect on a female's probability of admission in a pre-top 10 year at both universities (0.003 at Texas A&M and -0.001 at UT Austin). Second, the estimated coefficients on the interaction of male and gender imbalance are also close to zero and statistically insignificant, indicating that increases in the gender imbalance had no effect on a male's probability of enrollment prior to the top 10 plan. These results are consistent with the assumption that before the top 10 plan, universities were not required to admit the additional female students and, thus, not under pressure to manage the gender composition of the rank-ineligible applicant pool.

(Table 4 here)

Moving down the table, we see changes in the effect of the gender imbalance on admissions after the top 10 policy. First, the estimated coefficient on the interaction of gender imbalance and top 10 year suggests that a 100-female increase in the imbalance led to large negative effects on the probability that a female would be admitted (-0.056 for Texas A&M and -0.089 for UT Austin). Given that increases in the imbalance corresponded with increases in the total number of top 10 applicants that the universities were required to admit, these negative effects likely reflect capacity constraints at both universities. Second, and more importantly, the negative effect of the increasing gender imbalance was *less* negative for males than for females at Texas A&M as indicated by the positive coefficient on the three way interaction of male, gender imbalance, and top 10 year. At Texas A&M, a 100-person increase in the number of automatically-admitted females lowered a top 10 ineligible females' probability of admission by 0.056, while it lowered a male's probability by 0.033 (-0.056 + 0.023). In contrast, increasing gender imbalances had the same effect on male and female admissions at UT Austin. Unless the imbalance is correlated with unobserved traits that render male applicants to Texas A&M of higher quality than female applicants in post top 10 years when the gender imbalance increased (relative to pre to top 10 years), the results suggest preferential treatment of male applicants at Texas A&M.

The coefficients on the next 3 variables in Table 4 (male interacted with top 10 year, top 10 year, and male) have limited meaning given that there is no year in which the gender imbalance equals zero. The coefficient on male, for instance, suggests that in a pre top 10 year, when the gender imbalance is zero, males are more likely to be admitted at Texas A&M (by 0.061) and at UT Austin (by 0.067). In fact, the average gender imbalance in a pre top 10 year at Texas A&M is 4.9 (or 490 more females than males), and the gender difference in the probability of admission in these years is only 0.007. For UT Austin, the average gender imbalance is 4.0 and the male probability of admission is about 0.047 higher than the female probability of admission.

The results from Specification (2) are nearly the same as those from Specification (1), suggesting that the added covariates do not change the story. Importantly, and as we demonstrated above in our falsification tests, the results suggest zero or weak correlations between these covariates and the 3-way interaction of male, gender imbalance, and top 10 year. The similarities between the results of the 2 models lend further support to our assumption that the increasing gender imbalance in automatically-admitted students is exogenous to applicant characteristics that drive admissions.

The estimated parameters on the control variables show the expected signs. A student with a higher SAT/ACT score is more likely to be admitted at each of the universities, while a student with a higher reported class rank is less likely to be admitted. Controlling for test scores and class rank, blacks and Hispanics are more likely to be admitted (the other race category includes American Indians and students who self-identified as "other").[8] International students are also less likely to be admitted, consistent with university quotas on international students that render admissions highly competitive for this group.[9]

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[8] The non-zero coefficients on the race variables have two explanations. First, the data include pre-*Hopwood* years when affirmative action was legal. Second, though *Hopwood* prevents universities from considering applicant's race, they are permitted to consider characteristics that correlate with applicant race, such as ability to speak Spanish, socioeconomic status, and single-parent household.

[9] UT Austin, for instance, reports that "International applicants compete with each other for a limited number of international student spaces, rather than against all other freshman applicants (international students who qualify as Texas residents are an exception). Admission for international freshmen can be highly competitive." http://bealonghorn.utexas.edu/freshmen/after-you-apply/applicant-types.

The results from Table 4 are consistent with the interpretation that Texas A&M is responding to the mandate to admit females in the top 10 by disproportionately admitting males in the top 10 ineligible pool, possibly to maintain gender balance. Before proceeding with this interpretation, we undertake a number of robustness checks, the results of which are provided in Table 5 (Panel A for Texas A&M and Panel B for UT Austin). Column (1) of Table 5 reprints the coefficients and standard errors on the 3-way interaction from Specification (2) in Table 4 to ease comparisons. Column (2) provides results from the same model except that we estimate the regression using a probit regression (and report marginal effects). Column (3) provides the results when we include year of application fixed effects (and, correspondingly, remove the variables top 10 year and gender imbalance, which do not vary within year) to more adequately control for differences across years in applicant pools and admissions policies. Column (4) provides the results when we multiply impute high school class rank, combined SAT/ACT, and ethnicity data for the applicants who are missing data on these variables.[10] Column (5) provides the results when we drop 1997 applicants from the model. This was an unusual year as it followed the *Hopwood* decision of 1996 (which eliminated affirmative action) and preceded the top 10 policy. As a result, the applicants in this year were less likely to be from traditionally-underrepresented minority groups (Lisa Dickson 2006a) and admissions officers may have weighted applicant characteristics differently in an effort to maintain black and Hispanic enrollments (Mark C. Long and Marta Tienda 2008).

(Table 5 here)

The original results are largely robust to these alternative models with some slight variation. The probit model produces a larger coefficient than the linear probability model,

[10] We impute the missing values using multiple imputation by chained equations (Royston, 2004; Rubin, 1987) creating 10 multiply-imputed datasets and combining the results.

possibly due to the inaccuracy of the estimates on interaction terms from the probit models (Chunrong Ai and Edward C. Norton 2003). In addition, dropping 1997 leads to a slightly lower estimated coefficient on the 3-way interaction, yet it remains positive and statistically significant.

We estimated two additional robustness checks that are omitted from the manuscript to conserve space but available upon request. First, we estimated Equation (1) with more applicant-level controls in the Texas A&M sample, including Advanced Placement test performance and extracurricular activities (e.g. athletics, band). The estimated coefficient on the 3-way interaction in this additional specification is 0.021 (and the standard error is 0.006), very similar to the results from the original specification. Second, we obtained 4 years of post-top 10 applicant data on the state's most selective private university (Rice University). The mean gender imbalance in top 10 applicants was much smaller at Rice than at the two public flagships (an average of 80 more females than males) but the variation was wide (ranging from 20 to 150 students). We estimated a regression similar to Equation (1) for applicants to Rice University except that we removed the top 10 variable and all interactions with the top 10 variable given that the data were only available for post-top 10 applicants. The estimated coefficient on the 2 way interaction of gender imbalance and male was 0.008 with a standard error of 0.015, suggesting no effect of the gender imbalance at this private institution. Though the time series is short and the variation in the gender imbalance is small, the absence of an effect of the gender imbalance at Rice lends support to the assumption that there were no statewide changes in the quality of male and female applicants to selective universities in the years when the gender imbalances were large. If the effect of the gender imbalance on male's probability of admission to Rice (a university that is unconstrained by the top 10 rule) were nonzero, for instance, this would suggest that something other than the pressures created by the policy might be driving the observed results.

Thus far, our results suggest evidence of gender sensitivity in admissions at Texas A&M. Yet the estimated coefficient of 0.02 on the 3-way interaction term tells us little about how many students are potentially impacted by gender sensitive admissions practices. To evaluate the magnitude, we first use Equation (1) to compute the predicted probability of admission for the average male applicant in each post-top 10 year. We then generate the same predicted probabilities from Equation (1) after constraining the estimated coefficients on the 2 variables that interact male with gender imbalance (the 3-way interaction of male, gender imbalance, and top ten as well as the 2-way interaction of male and gender imbalance) to zero. In other words, our second set of predictions apply the female coefficients on the gender imbalance variables to determine male's probability of admission if the gender imbalance affected males and females equally. In 2002, when the gender imbalance was at its highest (approximately 1,020 more females than males), the predicted probability of admission for the average rank-ineligible male was approximately 0.52 using the estimates from Equation (1). The constrained predictions (using the coefficients on gender imbalance for females to produce male predictions), suggest that the predicted probability of admission would have been approximately 0.41 if males and females were affected equally by the imbalance. Approximately 5,348 rank-ineligible males applied to Texas A&M in 2002, which translates to nearly 580 more males being admitted than they would have been if the gender imbalance lowered their probability of admission by the same amount that it lowered females probability of admission. In other top 10 years, the gender imbalance was lower and, thus, the number of males who potentially benefited was also lower. For instance, in 1999, the gender imbalance was 6.31 and the number of males who potentially gained admission was 309.

B. Heterogeneity by Race/Ethnicity

As explained in Section I, the top 10 policy was enacted one year after the *Hopwood* decision, which banned race-based affirmative action. The initial purpose of the policy was to remedy race-based gaps in applications, admissions, and enrollments at the selective public universities in the state. Given the racial context of the law, we consider the effects of the policy on gender sensitivity within racial/ethnic groups.

Table 6 provides the results from Equation (1) for Texas A&M (in Panel A) and UT Austin (in Panel B). The results for Texas A&M suggest gender sensitivity among all groups except Asians. In addition, the estimated effect among black students is relatively large: a 100 female increase in the imbalance associates with a 5.3 percentage-point boost in rank-ineligible, black, male admissions. At UT Austin, we see no signs of gender sensitivity in admissions, even within the racial groups.

(Table 6 here)

The explanation for the differences at Texas A&M may lie in Table 7, which provides the gender imbalance in enrollments and applicants within racial/ethnic groups before and after the top 10 policy. To begin, we see wide variation in gender imbalances among enrolled students by race/ethnicity that is consistent with national trends (American Council on Education 2006). For instance, before top 10 at Texas A&M, only 41.8 percent of enrolled Asian students were female compared to 57.5 percent of enrolled black students. The same patterns are shown at UT Austin. After top 10, the enrolled populations became substantially more female for each racial/ethnic group; at Texas A&M, the female share of Asian students, for example, grew by almost 8 percentage-points. Yet, even after the top 10 plan, males outnumber females among Asian students.

Moving to the applicant pool, we see females dominating the rank-eligible group within all racial/ethnic groups (with the exception of Asians in the pre top 10 years). In addition, the female share of automatic admits increased by 2 to 5 percentage-points for all groups from before to after top 10. The patterns for whites and Hispanics are very similar with slight female majorities in the overall population and slight female majorities among automatic admits. Taken together, these results show much larger numbers of black females on campus (and in the automatically admitted pool) and much lower numbers of Asian females on campus (and in the automatically admitted pool). Thus, to the extent that administrators are concerned about gender imbalances, we would expect them to react most to the imbalance among black students and least to the imbalance among Asian students, where white and Hispanic students would rank somewhere in the middle. The estimated coefficients for Texas A&M from Table 6 are consistent with this expectation.

(Table 7 here)

C. Discussion

Our investigation has led us to a finding that requires further discussion. We searched for signs of gender sensitivity in admissions at two public flagship universities that are both faced with expanding enrollments and a state law that inadvertently requires them to admit more females than males. We find slight evidence of gender sensitivity at one of the two institutions (Texas A&M), but not the other (UT Austin). Why?

One possibility is that the rank-ineligible male applicants to Texas A&M were stronger in post-top 10 years when the automatically-admitted female population grew. Our effort to examine this question in Table 3 did reveal a slightly higher high school class rank for male students at Texas A&M in these years. Though statistically significant, however, the magnitude of the difference (0.3 of a percentage-point on a 100-point scale) lends little support to the theory that the 2.0 percentage-point boost in admissions was driven by much higher quality male applicants.

A second possibility is that the two universities simply employ different admissions practices and weight applicant characteristics differently. While UT Austin may be uniquely concerned with the racial/ethnic composition of its students given its location in an urban area, Texas A&M might have an added gender concern given its agricultural and military history. Texas A&M was initially named the Agricultural and Mechanical College of Texas, specializing in agriculture and requiring the study of military tactics. Today, Texas A&M remains one of only 6 senior military colleges in the country, which are colleges that are recognized by the U.S. law and Army Code.[11] As part of the requirements of a senior military college, the university must maintain a corps of cadets that meets the same military standards as those met at the service academies. In the 2009-2010 academic year, approximately 12 percent of the 1,730 corps of cadets at Texas A&M were women.[12] The gender difference in participation in the cadets and the military tradition at Texas A&M may factor into admissions decisions. Put differently, the infrastructure at Texas A&M may depend upon a minimum number of males on campus.

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[11] The other military colleges are: Virginia Military Institute (VMI), Virginia Polytechnic Institute and State University (Virginia Tech), The Citadel, Norwich University, and North Georgia College & State University.

[12] Texas A&M University Corps of Cadets Briefings Status Report End of School Year 2009-2010. Available online at: http://corps.tamu.edu/images/stories/pdfs/END_OF_YEAR_REPORT_09_10_100614.pdf

IV. Conclusions

Given the tremendous growth in female high school graduation and college enrollment rates over the past 30 years, concern is growing over the gender imbalance on college campuses across the country. Many college administrators have expressed concern over the new gender ratio and some in private colleges have conceded that they lower their admissions standards for male applicants in order to maintain gender balance in enrollments (Nancy Gibbs 2008). One study also provides empirical evidence that admissions favor male applicants to private liberal arts colleges when the female applicant pool increases (Sandy Baum and Eban Goodstein 2005). Little is known about how public universities are responding to the new gender ratio, however.

In this paper, we use administrative data from applicants to the two most selective public institutions in Texas to determine whether the universities give preference to males in the admissions process. Our estimation takes advantage of the passage of the Texas top 10 policy, which guarantees students who graduate in the top decile of their high school class from a Texas high school acceptance to any public university in Texas. Since the automatic admits are disproportionately women (due to their higher high school grades), we investigate whether universities respond to the imbalance in automatic-admits by boosting acceptance rates for male students who do not qualify for the policy. We find that an increase in the number of females in the top 10 who apply increases the probability of admission for males who apply to one of the two most selective public institutions in the state.

References

Ai, Chunrong and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economic Letters*, 80: 123-129.

American Council on Education. 2006. *Gender Equity in Higher Education: 2006.* American Council on Education Center for Policy Analysis.

Andrews, Rodney, Vimal Ranchod, and Viji 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.

Baum, Sandy, and Eban Goodstein. 2005. "Gender Imbalance in College Applications: Does it Lead to a Preference for Men in the Admissions Process?" *Economics of Education Review*, 24(6): 665-675.

Britz, Jennifer Delahunty. 2006, March 23. "To All the Girls I've Rejected." *New York Times*, Op-Ed. Accessed April 7, 2011. Available online at: http://www.nytimes.com /2006/03/23/opinion/23britz.html?_r=1.

Card, David, and Alan B. Krueger. 2005. "Would the Elimination of Affirmative Action Affect Highly Qualified Minority Applicants? Evidence from California and Texas." *Industrial and Labor Relations Review*, 58(3): 416-434.

Cardenas, Jose. 2007, February 5. "Where Are the College Guys?" *St. Petersburg Times (Florida),* pp. 1B. Accessed April 7, 2011. http://www.sptimes.com/2007/02/04/State/Where_are_the_college.shtml.

Conger, Dylan and Mark Long. 2010. “Why Are Men Falling Behind? Explanations for the Gender Gap in College Outcomes.” *The ANNALS of the American Academy of Political and Social Science*, 627(1): 184-214.

De Vise, Daniel. 2009. "Sex Bias Probe in Colleges' Selections." *Washington Post*

Accessed April 7, 2011. Available online at: http://www.washingtonpost.com/wp dyn/content/article/2009/12/13/AR2009121302922.html.

Dickson, Lisa. 2006a. "Does Ending Affirmative Action in College Admissions Lower the Percent of Minority Students Applying to College? *Economics of Education Review,* 25(1): 109-119.

Dickson, Lisa. 2006b. "The Changing Accessibility, Affordability and Quality of Higher Education in Texas." In *What's Happening to Public Higher Education?,* ed., Ronald Ehrenberg, 229-250. Westport, CT: Praeger Publishers.

Dorans, Neil J. 2002. "The Recentering of SAT Scales and its Effects on Score Distributions and Score Interpretations." The College Board, NY, Research Report No. 2002-11.

Franzese, Debra. 2007. "The Gender Curve: An Analysis of Colleges' Use of Affirmative Action Policies to Benefit Male Applicants." *American University Law Review*, 56(3): 729-750.

Gibbs, Nancy. 2008. "Affirmative Action for Boys." *Time* (Thursday April 3). Accessed April 7, 2011. http://www.time.com/time/magazine/article/0,9171,1727693,00.html

Greisemer, Nancy. 2011. "Civil Rights Commission suspends investigation into admissions discrimination." *Examiner.com* Accessed April 15, 2011. Available online at: http://www.examiner.com/college-admissions-in-washington-dc/civil-rights-commission-suspends-investigation-into-admissions-discrimination.

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

Hinrichs, Peter. Forthcoming. "The Effects of Affirmative Action Bans on College Enrollment, Educational Attainment, and the Demographic Composition of Universities." *Review of Economics and Statistics.*

Hussar, William J., Tabitha M. Bailey. 2011. *Projections of Education Statistics to 2019* (NCES 2011-017). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Jacob, Brian A. 2002. "Where the Boys Aren't: Non-cognitive Skills, Returns to School and Gender Gap in Higher Education." *Economics of Education Review*, 21(6): 589-598.

Jaschik, Scott. 2009, April 6. "10% Admissions - the Full Impact," *Inside Higher Education* Accessed April 7, 2011.
Available online at: http://www.insidehighered.com/news/20.

Kane, Thomas J. 1998. "Racial and Ethnic Preferences in College Admissions." In *The Black White Test Score Gap*, eds. Christopher Jencks and Meredith Philips, 431-456. Brookings Institution Press: Washington DC.

Kowarski, Ilana. 2010. "Civil-Rights Commission May Not Name Colleges in Admissions Report." *The Chronicle of Higher Education.* August 1, 2010
Accessed April 15, 2011. Available online at: http://chronicle.com/article/Civil-Rights-Commission-May/123737/

Lewin, Tamar. 2006. "At Colleges, Women Are Leaving Men in the Dust." *The New York Times*. Accessed April 25, 2011. Available online at: http://www.nytimes.com /2006/07/09/education/09college.html?_r=1.

Long, Mark C. 2004a. "College Applications and the Effect of Affirmative Action," *Journal of Econometrics*, 121(1-2): 319-342.

Long, Mark C. 2004b. “Race and College Admissions: An Alternative to Affirmative Action?” *The Review of Economics and Statistics*, 86(4): 1020-1033.

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: 48-66.

Owens, Jayanti. 2010. "Foreign Students, Immigrants, Domestic Minorities and Admission to Texas' Selective Flagship Universities Before and After the Ban on Affirmative Action." *Peabody Journal of Education* 85: 486-510.

Niu, Sunny Xinchun, Teresa Sullivan, and Marta Tienda. 2008. "Minority Talent Loss and the Texas Top 10 Percent Law." *Social Science Quarterly* 89(4), 831-845.

Niu, Sunny Xinchun and Marta Tienda. 2010. "The Impact of the Texas Top 10 Percent Law on College Enrollment: A Regression Discontinuity Approach." *Journal of Policy Analysis and Management* 29(1), 84-110.

Royston, Patrick. 2004. Multiple Imputation of Missing Values. *The Stata Journal*, 4, 227-241.

Rubin, Donald B. 1987. Multiple Imputation for Nonresponse in Surveys. New York: John Wiley and Sons.

Texas A&M. Texas A&M University Corps of Cadets Briefings Status Report End of School Year 2009-2010. Accessed April 21, 2011. Available online at: http://corps.tamu.edu /images/stories/pdfs/END_OF_YEAR_REPORT_09_10_100614.pdf.

The University of Texas at Austin, Office of Admissions. 2008. Implementation and Results of the Texas Automatic Admissions Law (HB 588) at the University of Texas at Austin.

Accessed March 28, 2011. Available online at http://www.utexas.edu/student/admissions/research/HB588-Report11.pdf.

Tienda, Marta and Teresa. A. Sullivan. 2009. "The Promise and Peril of the Texas Uniform Admission Law." In Martin Hall, Marvin Krislov and David L. Feathermen (eds.), *The New Twenty Five Years? Affirmative Action and Higher Education in the United States and South* Africa. Ann Arbor: University of Michigan Press.

Tierney, John. 2006. "On Campus, A Good Man is Hard to Find." *The New York Times*. Accessed April 25, 2011. Accessed February 12, 2011. Available online at: http://select.nytimes.com/2006/03/25/ opinion/25tierney.html?n=Top%2fOpinion%2fEditorials%20and%20Op-Ed%2fOp-Ed%2fColumnists%2fJohn%20Tierney.

United States Army. Army Regulation. Accessed April 21, 2011. Available online at: http://armypubs.army.mil/epubs/pdf/R145_1.PDF.

Table 1: Summary Statistics on Applicants and Admissions

	Texas A&M		UT Austin	
	Pre top ten policy	Post top ten policy	Pre top ten policy	Post top ten policy
Years available	1992-1997	1998-2002	1990-1997	1998-2003
Number of applicants (in 1,000s)	14.1	15.8	14.8	17.9
Percent of applicants who are eligible for top 10 policy	36.8	36.1	36.7	39.8
Percent admitted	75.8	72.3	70.9	67.6
Percent of enrolled who are female	49.3	51.4	48.4	52.4
Percent of top 10 eligible applicants who are female	55.1	57.9	54.5	57.5
Number of top ten eligible females - number of top ten eligible males (in 100s)	4.9	8.1	4.0	8.7
(Minimum - maximum)	(2.1 - 6.1)	(6.3 - 10.2)	(1.9 - 6.1)	(7.1 - 11.7)

Notes: i) Mean values across the years available are reported in cells. Minimum to maximum values across the years are reported in parentheses.

Table 2: Characteristics of Top Ten Ineligible Applicants, All Years

	Texas A&M			UT Austin		
	All	Male	Female	All	Male	Female
Male	1.00	0.55	0.45	1.00	0.53	0.47
Combined SAT/ACT score (in 100s)	11.20	11.38	10.97	11.51	11.76	11.24
(standard deviation)	1.40	1.42	1.34	1.47	1.47	1.41
High school class rank	27.20	29.14	24.85	27.09	28.91	25.03
(standard deviation)	16.37	17.27	14.88	16.43	17.24	15.21
White	0.76	0.75	0.77	0.66	0.65	0.66
Hispanic	0.11	0.11	0.11	0.15	0.15	0.15
Asian	0.06	0.06	0.05	0.13	0.13	0.12
Black	0.05	0.04	0.05	0.05	0.05	0.06
Other non-international race	0.02	0.02	0.02	0.01	0.01	0.01
International	0.01	0.01	0.01	0.01	0.01	0.01
Number of applicants	92,759	50,865	41,894	102,442	54,452	47,990

Notes: i) Means are reported in the cells. Standard deviations are reported in parentheses. ii) International is a racial/ethnic category.

Table 3: Falsification Tests

Dependent Variable	Combined SAT/ACT	High school class rank	White	Private high school	Size of high school class
Texas A&M	0.029	-0.293**	0.000	0.002	-1.081
	(0.017)	(0.113)	(0.003)	(0.001)	(2.120)
Observations	92,759	92,759	92,759	92,759	92759
UT Austin	0.009	-0.191	0.001	0.002	-1.244
	(0.009)	(0.116)	(0.003)	(0.002)	(0.909)
Observations	102,442	102,442	102,442	102,442	102442

Notes: i) The sample is restricted to students who are ineligible for the top 10 percent plan. ii) The dependent variable in each of the regressions is presented in the column headings. iii) The estimated coefficients (and standard errors) are the coefficient on the interaction of male, gender imbalance in top ten applicants, and top ten year. Gender imbalance is equal to the number of female applicants in the top 10 eligible applicant pool minus the number of male applicants in the top 10 eligible applicant pool (in 100s). iv) The regressions also include the interaction of male and top ten year, the interaction of top ten year and gender imbalance, gender imbalance, top ten year, and male. v) * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table 4: Regressions of Admission

	Texas A&M		UT Austin	
	(1)	(2)	(1)	(2)
Gender imbalance	0.003	0.000	-0.001	-0.008
	(0.006)	(0.006)	(0.012)	(0.014)
Male *x* gender imbalance	-0.011	-0.009	-0.005	-0.003
	(0.007)	(0.005)	(0.005)	(0.005)
Gender imbalance *x* top ten year	-0.056**	-0.051**	-0.089***	-0.091***
	(0.024)	(0.022)	(0.017)	(0.019)
Male *x* gender imbalance *x* top ten year	0.023***	0.020***	0.010	0.008
	(0.007)	(0.006)	(0.006)	(0.006)
Male *x* top ten year	-0.166***	-0.147***	-0.112**	-0.095**
	(0.031)	(0.032)	(0.038)	(0.032)
Top ten year	0.405*	0.374*	0.710***	0.744***
	(0.214)	(0.198)	(0.118)	(0.128)
Male	0.061*	0.063***	0.067***	0.026
	(0.030)	(0.018)	(0.019)	(0.022)
Combined SAT/ACT score (in 100s)		0.103***		0.139***
		(0.008)		(0.011)
High school class rank		-0.012***		-0.010***
		(0.000)		(0.001)
Hispanic		0.111*		0.103***
		(0.052)		(0.032)
Asian		-0.066***		0.018
		(0.016)		(0.012)
Black		0.148**		0.134***
		(0.063)		(0.035)
Other non-international race		-0.029**		-0.042***
		(0.010)		(0.011)
International		-0.142***		-0.109**
		(0.031)		(0.047)
Observations	92,759	92,759	102,442	102,442

Notes: i) The sample is restricted to applicants who are ineligible for the top 10 percent plan. ii) Specification (2) also controls for high school fixed effects (6,273 for Texas A&M and 5,196 for UT Austin). iii) Gender imbalance is equal to the number of female applicants in the top 10 eligible applicant pool minus the number of male applicants in the top 10 eligible applicant pool (in 100s). iv) * p<0.10; **p<0.05; ***p<0.01.

Table 5: Alternate Regressions of Admission

	(1)	(2)	(3)	(4)	(5)
Specification	Original	Probit regression	Year fixed effects	Missing data multiply imputed	Year 1997 dropped
Panel A: Texas A&M					
Male *x* gender imbalance *x* top ten year	0.020***	0.033***	0.021***	0.018***	0.017**
	(0.006)	(0.009)	(0.006)	(0.007)	(0.007)
Observations	92,759	75,447	92,759	93,114	84,149
Panel B: UT Austin					
Male *x* gender imbalance *x* top ten year	0.008	0.009	0.007	0.008	0.003
	(0.006)	(0.008)	(0.006)	(0.005)	(0.004)
Observations	102,442	86,724	102,442	113,348	96,001

Notes: i) The sample is restricted to applicants who are ineligible for the top 10 percent plan. ii) The table shows the estimated coefficients (and standard errors) on the interaction of male, gender imbalance, and top ten year. iii) Regressions also control for student's SAT/ACT score, high school class rank, and race/ethnicity as well as high school fixed effects. iv) Specification (2) omits observations for which there is no variation on the dependent variable within high schools. v) * p<0.10; **p<0.05; ***p<0.01.

Table 6: Regressions of Admission by Race/Ethnicity

	(1)	(2)	(3)	(4)	(5)
	All applicants	White	Hispanic	Asian	Black
Panel A: Texas A&M					
Male *x* gender imbalance *x* top ten year	0.020***	0.019**	0.018**	-0.001	0.053***
	(0.006)	(0.008)	(0.006)	(0.020)	(0.015)
Observations	92,759	70,495	10,257	5,271	4,257
Panel B: UT Austin					
Male *x* gender imbalance *x* top ten year	0.008	0.011	0.001	0.002	0.029
	(0.006)	(0.007)	(0.006)	(0.008)	(0.017)
Observations	102,442	67,478	15,374	12,907	5,353

Notes: i) The sample is restricted to applicants who are ineligible for the top 10 percent plan. ii) The table shows the estimated coefficients (and standard errors) on the interaction of male, gender imbalance, and top ten year. iii) Regressions also control for student's SAT/ACT score, high school class rank, as well as high school fixed effects. iv) * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table 7: Summary Statistics on Applicants by Race/Ethnicity

	Texas A&M		UT Austin	
	Pre top ten policy	Post top ten policy	Pre top ten policy	Post top ten policy
White applicants				
Percent of enrolled who are female	49.9	52.0	48.5	52.6
Percent of top 10 eligible applicants who are female	55.8	58.2	54.4	57.2
Hispanic applicants				
Percent of enrolled who are female	47.1	51.0	47.8	52.9
Percent of top 10 eligible applicants who are female	53.0	56.3	54.0	56.8
Asian applicants				
Percent of enrolled who are female	41.8	49.3	46.9	49.6
Percent of top 10 eligible applicants who are female	48.4	53.7	53.2	55.9
Black applicants				
Percent of enrolled who are female	57.5	60.7	54.8	60.1
Percent of top 10 eligible applicants who are female	64.6	66.2	66.5	69.6

Notes: i) Mean values across the years are reported in cells.