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The Impact of the Texas Top 10% Law on College Enrollment: A Regression Discontinuity Approach

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Introduction

In response to the 5th Circuit Court's 1996¹ judicial ban on the use of race-sensitive criteria in college admissions decisions, the Texas legislature passed H.B. 588—popularly known as the top 10% law—guaranteeing automatic admission to any public university of choice to students who graduate in the top decile of their class. Designed to restore diversity to the public flagships following the ban on affirmative action, the top 10% law establishes a uniform merit criterion, namely class rank, and applies it uniformly across schools.

Supporters of the Texas top 10% regime herald it as a merit-based alternative to affirmative action, emphasizing that the law leveled the playing field in access to the public flagships, but cautioning that additional outreach and scholarship programs are necessary for their success (Walker and Lavergne, 2001). Opponents allege that the percent plan not only disguises the use of race in admissions, but also distorts the role of merit in college admissions because the top decile graduates from high and low performing schools may not master similarly rigorous curricula.² Rather than privileging

¹ *Hopwood v. University of Texas* 78 F.3d 932, 944 (5th Cir. 1996).

² Although the percent plan is technically race neutral, it requires segregation to be maximally effective in restoring and maintaining campus diversity (Flores and Horn, 2003; Tienda and Niu, 2006b).

individual students on the basis of ascribed characteristics, as critics of affirmative action claim, opponents of the top 10% law argue that use of a single measure of merit advantages students from underperforming *schools*. In effect, Texas altered the terms of the debate about equity in access to selective post-secondary institutions by changing the exclusion criteria from individual attributes—namely race and Hispanic origin—to high school characteristics, notably ethno-racial composition, which determines the likelihood that minority students will qualify for the guarantee, and high school affluence, which influences the likelihood of enrollment, other things equal (Tienda and Niu, 2006b; Niu, et al., 2006).

Administrators and legal experts mainly monitored enrollment trends for underrepresented minority groups after the judicial ban on affirmative action, but there is evidence that the change in admission regimes also influenced application trends (Kain, O'Brien and Jargowsky, 2005; Brown and Hirschman, 2006). Studies that seek to evaluate how the change from affirmative action to the uniform admission regime influenced trends in minority college enrollment fall into two general classes—those based on administrative data before and after the policy change (Montejano, 2001; Long and Tienda, 2007; Card and Krueger, 2005; Alfonso and Calcagno, 2006), and those based on longitudinal survey data (Tienda and Niu, 2006a; 2006b).

Several studies reported declines in minority applications and admissions at the University of Texas at Austin and Texas A & M University after the Hopwood decision took effect (Walker and Lavergne, 2001; Chapa and Lazaro, 1998; Card and Krueger, 2005; Horn and Flores, 2003). Because enrollment trends depend on applications as well as the odds of admission, researchers have also considered how changes in admission

regimes influence all three outcomes. For example, in Washington State, Brown and Hirschman (2006) found that Initiative 200 lowered minority enrollment largely through the drop in applications. But in California, Lomibao and associates (2004) claim that the lower representation of minority students following the public referendum banning affirmative action resulted not from the lower volume of applications from minority students, which actually rose steadily, but rather from their lower odds of admission.

Two recent studies exploit the “natural experiment” in Texas college admissions by using administrative data to examine whether and how admission and enrollment probabilities changed after affirmative action was judicially banned. Long and Tienda (2006) consider whether the top 10% law succeeded in maintaining minority admission rates at their pre-*Hopwood* levels at three Texas public universities that differ in the selectivity of their admissions, and conclude the percent plan is an ineffective proxy for race-sensitive criteria in college admissions.³ Examining application, admission and enrollment trends at three Texas public institutions,⁴ Alfonso and Calcagno (2006) show how demographic trends contributed both to the observed shifts in the composition of applicants and enrolled students.

While instructive, studies based on administrative records can not consider the range of alternatives that students considered in their college decision-making. Using survey data, Niu et al. (2006) have examined both how institutional characteristics influence students’ college preferences and enrollment behavior under the uniform admission regime, noting that distance, cost and availability of financial aid are important determinants of matriculation decisions. In another analysis, Niu and Tienda (2006)

³ Long and Tienda also consider two private institutions, Rice and Southern Methodist University, but for these institutions the data is limited to the period that the uniform admission law was in effect.

⁴ TAMU, Texas Tech, and TAMU-Kingsville.

consider how high school characteristics influence college choice. They find that type of high school attended is more salient than class rank in delimiting students' choice sets, which in turn delimits enrollment outcomes.

These two studies based on survey data suffer from two limitations. First, because class rank is self-reported - either unknown or estimated by a significant number of students - inferences about its influence on post-secondary outcomes are approximate. A more significant drawback is their inability to draw causal inferences about the influence of the uniform admission regime on enrollment outcomes owing to the lack of a comparison group whose admission was not governed by the top 10% law.

Accordingly, this analysis addresses both limitations first by using transcript-verified class rank information, and second applying a regression discontinuity technique to estimate the impact of the Texas top 10% law on college enrollment decisions of rank-eligible students. Specifically, we assess the law's impact on four nested college enrollment decisions by asking whether the uniform admission law increases the likelihood that top 10% graduates enroll (1) at any post-secondary institution; (2) at a 4-year institution; (3) at a Texas 4-year post-secondary institution; and (4) at one of the Texas public flagships? By combining the richness of the survey data and the simulated quasi-experimental design, we improve upon analyses that use either approach alone.

The Texas uniform admission law also raises questions about access to higher education that transcend the instrumental goal leading to its implementation. Specifically, the shift from a race-conscious admissions regime to a percentage plan has testable implications about how the likelihood of enrollment will differ for rank-eligible students who differ in their racial attributes and the types of high schools they attend. Therefore,

we evaluate whether the impact of the top 10% law differs for underrepresented minority and white students, and those who graduate from schools that differ in their ethno-racial composition and affluence.

Following a discussion of the data and the regression discontinuity technique, we present probit estimates for the impact of the top 10% law on the four outcomes of interest for the total sample, and separately for race and ethnic groups and high school strata. We find that, rank-eligible seniors are more likely to enroll in college, and also more likely to enroll in a 4-year institution as a result of the top 10% law. However, the boosting effect on 4-year enrollment is diminished for those close to the cutoff point. Moreover, while the top 10% law raises 4-year college enrollment among top decile white students, it also boosts overall college enrollment of rank-eligible minority students, as well as their enrollment at 4-year institutions.

Data and Methods

The empirical analyses are based on the senior cohort of the Texas Higher Education Opportunity Project (THEOP) survey data, a representative, longitudinal study of Texas public high school students who were first surveyed during spring of 2002 using a paper and pencil in-class survey instrument (N=13,803).⁵ For cost reasons, the longitudinal sample is based on a random subsample of the baseline respondents (N=5,836), who were re-interviewed by phone one year following high school graduation. To guarantee the maximum possible precision for blacks and Asians, all baseline respondents from these groups were included in the longitudinal sample;

⁵ The sampling scheme is described in detail in the “Methodology Report,” http://theop.princeton.edu/surveys/baseline/baseline_methods_pu.pdf

proportionate samples of Hispanics and non-Hispanic whites were randomly drawn for the sample balance. The response rate for the wave-2 interviews was 70 percent, and sample weights for the follow-up interviews were recalibrated to the original population.⁶

In addition to basic demographic, socioeconomic and standard tracking information, the baseline survey obtained self-reported information about grades, class rank, and future plans. The first follow-up survey (wave 2) recorded whether respondents actually enrolled in college one year after high school graduation, and if so, where. For students who participated in the second interview, self-reported class rank, standardized test scores, and high school GPA were subjected to a transcript verification procedure, which was conducted by high school administrators or staff. Over 90 percent of records were so verified; moreover, the transcript-based class rank is precisely measured, which is necessary for application of regression discontinuity techniques.

Key outcome variables

We examine the impact of the top 10% law on four nested college decisions: whether respondents enrolled in a post-secondary institution; whether college-goers enrolled in a 4-year institution; whether 4-year college enrollees attended a Texas institution; and whether the 4-year Texas college enrollees attended one of the public flagships. This nested scheme allows us to discern the impact of the law, which was restricted to Texas public institutions. Moreover, its impact is likely to be greatest at the most selective public institutions, the University of Texas at Austin (UT-Austin) and Texas A&M University at College Station (TAMU), which are the two institutions where affirmative action was most used before the judicial ban (THECB, 1998).

⁶ The sampling scheme is described in “Senior Wave 2 Survey Methodology Report,” http://theop.princeton.edu/surveys/senior_w2/senior_w2_methods_pu.pdf

Subgroups and high school strata

Although allegedly race-neutral, the top 10% law was designed to increase access to Texas selective public institutions for underrepresented minority groups. Therefore, we estimate the same specifications separately for white, black, Hispanic and Asian students. Furthermore, because the law's success in restoring campus diversity depends on the pervasiveness of school segregation (Tienda and Niu, 2006), we evaluate the impact of the law across school segregation strata. This indicator was obtained from administrative data posted by the Texas Education Agency and appended to individual records. Students were sorted into five strata based on the ethno-racial composition of their high schools, using the percent white as a baseline referent, namely:

- predominantly (more than 80%) white;
- majority (60-80%) white;
- integrated (40-60% white);
- majority minority (20-40% white);
- predominately minority (less than 20% white).

Lastly, admissions officers from the two public flagships acknowledged that the admission guarantee was insufficient to increase enrollment of underrepresented groups (Walker and Lavergne, 2001). Recognizing that vigorous outreach and scholarship programs were a necessary adjunct to successfully recruit high achieving students from low income and minority groups, administrators at UT-Austin and TAMU campuses targeted high schools with low college-going traditions and high shares of economically disadvantaged students. Designated Longhorn (UT) and Century (TAMU) high schools, rank-qualified students are offered scholarships to enable their attendance at the respective institution. Using average economic status and high or low college-going

tradition, we develop a 5-category typology of Texas high schools to evaluate the impact of the top 10% law. These are:

- *feeder high schools*: strong tradition of sending students to the two public flagships, and low shares of economically disadvantaged students;
- *affluent high schools*: low shares of economically disadvantaged students, average college-going tradition;
- *poor high schools*: high shares of economically disadvantaged students, average college-going tradition;
- *Longhorn/Century schools*: high shares of economically disadvantaged students, low college-going traditions and targeted for outreach and scholarship programs;
- *typical high schools*: average shares of economically disadvantaged students.

Although the high school segregation and economic strata overlap somewhat, they represent substantively different constructs. For example, typical high schools include predominately minority, integrated, and majority white high schools. Although none of the predominately minority schools are classified as affluent or feeder high schools, they include typical, poor and Longhorn/Century high schools.

The Regression Discontinuity Approach

To estimate the impact of the Texas top 10% law on college enrollment, we simulate the quasi-experimental conditions using a regression discontinuity (RD) approach. In their original paper, Thistlethwaite and Campbell (1960) studied two groups of near-winner students—one that was awarded Certificates of Merit and another that merely received letters of commendation based on qualifying scores—to estimate the effect of the Certificate of Merit on a student’s other scholarship receipt and career plans.

In this RD design, a single “treatment” divides subjects into the treated and untreated groups, namely receipt of the merit certificate. Therefore, a distinct discontinuity at the cut-off point provides evidence of the treatment effect. Presumably, other characteristics correlated with the probability of being treated trend smoothly through the cutoff point.

In education research, the RD design has recently been applied to estimate the effect of financial aid on college enrollment (Van der Klaauw 2000; Kane 2003); the effect of remedial education on student achievement (Jacob and Lefgren, 2004; Moss and Yeaton, 2006); and the impacts of failing the high school exit exam on eventually obtaining a diploma, attending college, and wages (Matorell 2004). The RD approach is well suited for our analytical objectives because the top ten percent law stipulates the exact cut-off point needed to implement the RD framework. In our application, the RD design is as follows:

$$y = g(\text{rank}) + \alpha_1 T + \alpha_2 T * g(\text{rank}) + \beta Z + \varepsilon, \quad \text{where } T=1 \text{ if } \text{rank} \leq 10 \quad (1)$$

In this specification, y indicates whether a student enrolled (0/1) in college; $g(\text{rank})$ is a continuous function of high school actual percentile class rank; T is the top 10% status indicator function; $T * g(\text{rank})$ represent interactions between T and $g(\text{rank})$; Z is a vector of individual characteristics affecting college enrollment outcomes; and ε is an error term. Students who rank below the 10% rank cut-point are placed in the control group ($T=0$), and students ranked at or above the 10% cut-point (percentile rank equal to the first decile) are placed in the treatment group ($T=1$).

In a sharp regression-discontinuity design, where all top decile students are placed in the control group, assignment coincides with treatment status, thus coefficient α_1 gives the intent-to-treat (ITT) effect. The ITT represents the average effect of making the program available to its targeted group, thus α_1 estimates the gains that policymakers would observe from implementing the program given certain levels of non-participation (Heckman, LaLonde and Smith, 1999). ITT is an important policy-relevant measure, but also represents a complex combination of the treatment effects for participants and non-participants.⁷

Assuming the error term ε in equation (1) is distributed normally, it can be estimated with a probit specification;

$$Prob(y=1) = \Phi(g(rank) + \alpha_1 T + \alpha_2 T * g(rank) + \beta Z), \quad (2)$$

then $prob(y=1|T=1) - prob(y=1|T=0)$ gives the estimated marginal intent-to-treat (ITT) effect of the 10% law on students' college enrollment. Because the estimated impact only applies to those near the cut-point, the impact of the law on students far away from the threshold may be quite different.

Polynomial Functional Form

College enrollment is assumed to be a continuous function of high school percentile class rank, $g(rank)$, but the estimates will be biased and/or inefficient if g is

⁷ In our case, the top 10% law guarantees automatic admissions to any public Texas universities of their choice to top decile students, but they need to know that they qualify for the admission guarantee and they need to apply and comply with application rules of universities to which they seek admission. The two flagships have application deadlines and require SAT scores even though they are not considered in admissions decisions. Thus, the knowledge of the law and the ability to comply with application rules leads to non-participation among top decile students, which means students are unable to take advantage of the admission guarantee. In the near future, we plan to model the participation status in order to estimate the policy effect for those who actually take advantage of the top 10% law.

misspecified. While over-specified models are unbiased, albeit inefficient, generally the under-specified models are both biased and inefficient. Therefore, when the functional form is misspecified, over-specification is preferred and under-specification should be avoided (Trochim, 1984).

We follow the strategies outlined by Trochim (2006) to specify alternative polynomial functional forms for each of the four outcome variables of interest. After visual inspection of the relationship between percentile class rank and college enrollment outcomes for n flexion points, we begin with $n+2$ order polynomial models, including interactions between polynomial terms and percentile class rank; subsequently, we refine models by removing extraneous terms, starting with the highest-order term. Models are re-estimated until the rank coefficient is significant, the goodness-of-fit measure drops appreciably, or the pattern of residuals indicates poor-fitting models. These refining processes yielded the following specifications of equation (1) for each of the outcome variables:

$$\text{Enrolled} = \text{rank} + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon; \quad (1a)$$

$$\text{Enrolled 4-year} = \text{rank} + \text{rank}^2 + \alpha_1 \cdot \text{Top10\%} + \alpha_2 \cdot (\text{Top10\%} * \text{rank}) + \beta Z + \varepsilon \quad (1b)$$

$$\text{Enrolled TX 4-year} = \text{rank} + \text{rank}^2 + \text{rank}^3 + \text{rank}^4 + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon; \quad (1c)$$

$$\text{Enrolled TX Flagship} = \text{rank} + \text{rank}^2 + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon; \quad (1d)$$

Unlike other researchers who use a single high-order specification for different outcome variables (Matorell 2004), for both theoretical and practical reasons we use different polynomial specifications for each of the four outcome variables. Theoretically,

the relationship between percentile class rank and the four college outcomes should differ because high class rank is positively related to the selectivity of college choices. A visual inspection of the association clearly reveals different relationships between percentile class rank and the four college enrollment outcome variables. From a practical standpoint, although the sample size is adequate for model specification, the top decile cut-point yields relatively small treatment groups, particularly for subgroup comparisons. Under these conditions, including too many unnecessary high order polynomial terms sometimes produces inefficient estimates of the program effect.⁸

Statistical controls

The probit models are estimated with and without the set of controls Z that are known to influence college enrollment: family SES variables (parental education and home ownership) and respondent's college disposition (grade level when respondent first considered college). The models without the controls are the baseline models. With few exceptions, inclusion of controls does not lead to substantive changes in estimates of the impact of the top 10% law on college-going. This result confirms an assumption needed for application of regression discontinuity technique, namely that observed student characteristics other than class rank trend smoothly through the cutoff-point.

⁸ The strategy of working downward from a high order polynomial functional form serves to check the robustness of the estimates obtained from final specifications detailed above. Appendix 1 details changes in coefficient estimates and pseudo R-Sq in varying polynomial specifications. Specifically, for college enrollment, similar estimates of the impact of the law are obtained with and without 2nd order polynomial and interaction terms, but the significance levels change. Among college goers, the estimates of the impact of the law on 4-year enrollment are quite large and statistically significant ($p \leq 0.01$) for specifications that include the 3rd order and lower polynomial and interaction terms. However, for the Tx 4-year and Tx Flagship outcomes, the model fails to attain statistical significance in specifications that include the 4th order and lower polynomial and interaction terms. In fact, signs of the estimates actually change in different specifications. Therefore, we are confident that the model specifications detailed above fit data appropriately and capture well the program effect when present.

Results

We first compare descriptive statistics for top decile students and those ranked at or below the 20th percentile to verify whether the basic assumption of regression-discontinuity design holds in our sample, namely whether in the absence of the treatment, students around the cutoff point will be similar. Table 1 presents sample means for students ranked in the top 10% and those ranked 20 to 100%. With a few exceptions, means of the post-secondary outcomes and student characteristics known to influence college enrollment differ statistically for the two groups when students from the full class rank distribution are considered. Significant differences in college enrollment, 4-year enrollment and flagships enrollment also hold when we compare students within a small interval around the cutoff point—6-10% versus 11-15%. However, while the differences in student characteristics known to influence college enrollment vanish with the exception of being Asian and having parents with less than high school education. When the interval is further narrowed to a 6 percent point range—8-10% vs. 11-13%—differences for overall enrollment and 4-year enrollment remain statistical significance, although the former borders on the margin of significance. Being Asian and having parents with less than high school education also remain significant, albeit the former is on the margin of significance.

Table 1 About Here

Although the eligibility rule is known and students near the cutoff point may work harder to improve their class rank, it is difficult for individual students or teachers to intentionally alter their position at the cutoff point. Furthermore, the eligibility is most meaningful for access to the two Texas public flagships, which require schools to report

students' class rank and the senior class size in order to calculate class rank percentile. Figure 1 presents the distribution of high school seniors by actual percentile class rank. Although the class rank distribution is upwardly skewed, no significant "clumping" appears around the 10th percentile class rank.⁹ The accumulative class rank distribution is smooth throughout.

Figure 1 About Here

The subsequent analyses estimate the intent-to-treat effect of the top 10% law on students' college-going, beginning with the pooled sample, and proceeding to group-specific estimates, namely by race and ethnic groups, segregation strata, and high school type. For each outcome of interest, we first present visual displays of the impact of the top 10% law on college enrollment and in the subsequent table report probit regression discontinuity estimates.

Figures provide visual evidence for discernable discontinuity in the relationship between class rank and the various college enrollment outcomes at the cut-point. The discontinuity can manifest itself either as a *vertical* change in *level* (main effect), a change in *slope* (interaction effect), or both. In each of the graphs, the open circles represent the average enrollment rate for students with a particular class rank, and the superimposed smooth lines are the predicted enrollment probability from a baseline probit specification discussed earlier. Overall, the graphs show that the predicted enrollment probabilities track the local averages reasonably well, and a discontinuity is visually discernable in most of the cases where the probit models yield statistically significant point estimates. The subsequent tables report probit regression discontinuity

⁹ The upward skew is inconsequential for the analysis, which only requires the absence of large clumping around the cutoff point.

estimates of the main intent-to-treat (ITT) effect of the top 10% law on various measures of college enrollment. We also report the estimates of the linear interaction terms, which are significant predictors of 4-year college enrollment outcomes. All estimates reported in the tables and figures are marginal effects calculated at the sample means for students at the cutoff point.¹⁰

College-Enrollment

Five noteworthy findings emerge from the empirical estimation. First, the top 10% law increases rank-eligible students' overall college enrollment, and conditional on their post secondary matriculation, the top 10% graduates are more likely to enroll in a 4-year compared with a 2-year institution. However, the boosting effect diminishes for students close to the cutoff point. The upper top two graphs in Figure 2 reveal a clear disjuncture at the cutoff point, with a 4 percentage point difference in college enrollment between students at the cutoff point and those just below. The estimated discontinuity at the cutoff point is about 6 percentage points among the subset of seniors who actually matriculated in college the year after high school graduation. This boost results both from a large statistically significant main effect, and a significant large interaction effect. As

¹⁰ There does not seem to be consensus about which sample means to use in calculations based on a probit specification. Of the two recent studies using an RD approach with a probit specification, Kane (2003) calculates the marginal effects at the sample means for all observations used in the estimation but Matorell (2004) calculates the marginal effects at the sample means for observations at the cutoff point. In this paper, we report the marginal effects at the sample means for students at the cutoff point to obtain discontinuity estimates for substantive reasons. Because the regression discontinuity approach focuses on the discontinuity at the cutoff point, which is established by law. The marginal effects should not be sensitive to which set of means are used if the cutoff point is around mean or the relationship between class rank and each outcome variable is flat. In our case, however, the mean class rank for all observations used in estimation are quite different from the cutoff point, Furthermore, the relation between the class rank and three outcome variables (enrolled, enrolled 4-year and enrolled in a flagship) manifest a significant slope. Therefore, the marginal effects calculated at the means for all observations used in the calculations tend to overstate the effects. Therefore, our calculations at the means for observations at the cutoff point are conservative.

later group-specific analyses reveal, the impact on overall college enrollment and 4-year enrollment largely derives from a boosting effect among rank-eligible minority students.

Figure 2 and Table 2 About Here

The top 10% law does not appear to boost in-state college enrollment among 4-year college goers, nor does it raise the likelihood of enrollment at the flagships among students who enroll at in-state 4-year institutions. Partly this reflects the fact that the vast majority of Texas high school graduates attend one of the state institutions, with distance and cost among the salient factors in their final choice. Although a disjuncture appears in the graph for in-state 4-year enrollment, a large standard error renders it an insignificant result. This result obtains in all subsequent group-specific analyses, where statistical significance of the ITT estimates is never reached. Nationwide, most of high school seniors remain in their home state for college education, but this is particularly so in Texas due to relatively low tuition rates (Leight and Sullivan, 2000). In fact, across entire class rank percentile range, in-state college enrollment is about 90 to 90 percent, and the top 10% law does not seem to influence whether top-ranked students leave the state for colleges (Tienda and Niu, 2006a). The disjuncture at the cutoff point for flagship enrollment is small at 0.02 and statistically insignificant, which partly reflects that substantial number of students just below top 10% threshold succeed in enrolling in flagships. However, unlike the case for in-state enrollment, top 10% law does appear to boost flagship enrollment for certain groups of students, as shown later.

That the top 10% law has a greater boosting effect on 4-year college enrollment compared with overall college enrollment, but no effect on flagship enrollment parallels a finding established by the financial aid literature. Financial aid increases college access

for marginal students who are deciding between enrollment at a 4-year versus a 2-year institution, but generally this choice does not carry over to enrollment at selective institutions, which represent a subset of the four-year choice.

Second, we find noteworthy race and ethnic differences in the impact of the law on enrollment probabilities. Specifically, as Figures 3 and 4 show, the top 10% law boosts 4-year college enrollment among rank-eligible white students, but for black and Hispanic students, it raises both overall college attendance and their enrollment at 4-year institutions. In Figure 3, the graph for white students' college enrollment shows no discontinuity at the cutoff point, and the graph displaying their 4-year enrollment probability reveals a small jump at the cutoff point. The latter results from a large main effect and a large, albeit statistically insignificant, interaction effect. Although a discontinuity is also evident for in-state, 4-year enrollment and flagship enrollment, the large standard errors nullify statistical significance. The negative (albeit insignificant) discontinuity at the cutoff point for flagship enrollment is intriguing because it also obtains for students from predominately white and majority white high schools, as we demonstrate below. Further investigation of their college destinations reveal that many of these students opt for a private in-state institution, where they have much stronger competitive edge compared with others ranked in the second decile.

Figures 3 and 4 About Here

Table 3 About Here

For black, Hispanic and Asian students, the point estimates, although quite large in magnitude in many cases, do not obtain significance due to large standard errors. The notable exception is overall college enrollment for Hispanics. Table 3 reports these

estimates, which are not displayed graphically. Assuming that the lack of statistical significance reflects the small sample sizes, we pooled blacks and Hispanics, the two under-represented minority groups, and re-estimated the model. Figure 4 displays these results, which are also reported in the far right column in Table 3. As expected, the increased sample size improves the statistical significance of the point estimates; substantively the results indicate that the top 10% law raises overall college enrollment and 4-year enrollment among rank-eligible black and Hispanic graduates, which is depicted by rather large jumps at the cutoff point in the top two graphs in Figure 4. Specifically, black and Hispanic students at the cutoff point are about 6 percentage points more likely to enroll in a college, and they are 18 percentage points more likely to enroll in a 4-year college (among college-goers) than their statistical counterparts ranked immediately below the cutoff point. A rather large discontinuity at the cutpoint also corresponds to flagship enrollment, shown in bottom-right graph. However, this ITT estimate is not statistically significant at the .05 level, only at the .10 level, which probably reflects the relatively small number of black and Hispanic students matriculating at the flagships. Still, this result suggests that top 10% law has some capacity to restore ethno-racial diversity at the state's public flagships (Walker & Lavergne, 2001; UT Office of Public Affairs, 2003). Its effectiveness in equalizing black and Hispanic students' access to Texas' selective public institutions, however, was limited even four years into its implementation (Kain et al., 2005, Long and Tienda, 2006).

Third, while college enrollment decisions of top decile graduates from white or integrated high schools are relatively un-affected by the top 10% law, top-ranked students

who graduated from predominantly minority high schools are more likely to enroll in college, to enroll in a 4-year institution, and to enroll at one of the public flagships. Given the design and intent of the law, this is a powerful result. Graphs in Figure 5 show no effect or a negative slope at the cutoff point for students from white schools, except for in-state enrollment where large standard errors nullify statistical significance. For students from integrated schools a small enrollment boost emerges for all enrollment outcomes (displayed in Figure 6), but none obtain statistical significance due to large standard errors. By contrast, the enrollment boost at the cutoff point is sizable and statistically significant for graduates from minority high schools, as shown in Figure 7 and detailed in Table 4. Specifically, at the class rank cutoff point, seniors from high schools where less than 20% students are white are 8 percentage points more likely to enroll in a post-secondary institution, 22 percentage points more likely to enroll at a 4-year institution, and 19 percentage points more likely to enroll at one of public flagships than those immediately below the cutoff point. Also, for students from majority minority schools, where between 20 and 40 percent of students are white, the difference in overall college enrollment between those at the cutoff point and those immediately below is 15 percentage points.

Figures 5 -7 and Table 4 About Here

That the point estimates derived from segregation strata parallel the results based on minority groups reinforces prior claims that most black and Hispanic students who achieve top 10% class rank hail from predominately minority schools (Tienda and Niu 2006b). However, the impact of the top 10% law on flagship enrollment among Black and Hispanic students is only marginally significant, which indicates that they are less

likely than whites to qualify for automatic admission, even if they attend segregated schools (Niu, Sullivan and Tienda, 2006). By design, the top 10% law capitalizes on school segregation to recruit black and Hispanic students to selective public institutions in Texas, and it does attract many top performing students from segregated schools. However, the law explicitly leaves the calculation of class rank to the discretion of individual high schools, and thus has no capacity to influence which students actually qualify for the admission guarantee.

Fourth, the top 10% law raises overall college enrollment and 4-year enrollment among top 10% students who graduate from high schools targeted for Longhorn and Century scholarships, although the 4-year enrollment boosting effect diminishes for those very close to the cutoff point. Although UT and TAMU target these high schools for outreach programs and limited scholarship offers to rank-qualified graduates, we fail to find direct evidence that the top 10% law boosts flagship enrollment among top decile students who graduated from these high schools.

The top-left graph in Figure 8 shows an 11 percentage point boost at the cutoff point for post secondary enrollment among Longhorn/Century school graduates. This boost is more than double that obtained for all seniors (Figure 2). The discontinuity is actually negative for 4-year enrollment due both to a large and significant main and significant interaction effects. That is, the boosting effect on 4-year enrollment diminishes steeply moving down the class rank to the cutoff point, and completely disappears for students from Longhorn/Century schools who are ranked at the 10th percentile. The diminished boosting effect raises a concern about college-going behaviors of these top performing students who are close to the cutoff point because it is

likely that, owing to financial considerations, many enroll at 2-year institutions with low chances of completing baccalaureate degrees.¹¹ The discontinuity for instate 4-year enrollment is negative and quite large in magnitude, though not statistically significant. Along with the case for students from minority schools, this exception probably reflects that top performing students from these schools are heavily recruited by out-of-state institutions.

Figure 8 and Table 5 About Here

Because the Longhorn/Century scholarship programs were designed by UT and TAMU to recruit top 10% graduates from these low income schools with low college-going traditions, we expected a significant boosting effect on enrollment in flagships among these students. Small case numbers lead to large variances, hence we are unable to model these students' enrollment at the public flagships with precision – the estimated discontinuity is small, negative and statistically insignificant. This likely reflects the designation of the handful of scholarships per school to the highest ranked among seniors who qualify for the guarantee. Only a limited number of scholarships are available at each of the Longhorn and Century high schools three to four per school, on average, and between 250 to 300 per year for each program (Domina, 2006). Owing to financial constraints of these students combined with low college-going traditions at these schools, we suspect that only the very top students receive financial support. Thus it is not surprising that our estimates cannot detect obvious discontinuities at the cut-off point as implied by the top 10% law. We verified this hunch by examining the class rank distribution among graduates for Longhorn and Century schools who enroll flagships and

¹¹ Longhorn Century High Schools include large numbers of low-income students by design.

find that nearly three quarter of these students ranked in the top 7th percentile or better of their graduating class while 80 percent of these students rank in the top 10%.¹²

Nevertheless, examining this finding against an earlier result – namely that top 10% students from predominately minority schools are more likely to enroll at one of public flagships – is very telling. Although Longhorn and Century high schools enroll mostly minority students, at many minority high schools the share of economically disadvantaged students hovers around the statewide average. Therefore, our discontinuity estimates are entirely consistent with claims that concentrated economic disadvantages, not the race/ethnic segregation per se, drives the low flagships enrollment rates of minority students (Tienda and Niu, 2006b).

It bears emphasizing that our failure to find the significant boosting effect of the top 10% law on flagship enrollment among top 10% graduates from Longhorn/Century high schools DOES NOT mean that the outreach efforts and targeted scholarship programs are inconsequential for flagship enrollment among students who are eligible for the admission guarantee. Although we do not formally test the differences in estimates across groups, comparing the large negative discontinuity at the cutoff point obtained for students who attend resource-poor schools and the small negative discontinuity at the cutoff point obtained for graduates from Longhorn/Century schools suggests that the scholarship programs do increase minority enrollment at the public flagships, as indicated by other studies (Niu, et al, 2006).

For high schools at the other end of the socioeconomic spectrum, such as feeder and affluent high schools, the top 10% law seems to have limited impact on their college-going decisions (graphs not shown, results reported in Table 5). However, the admission

¹² Administrative data from UT and TAMU further confirms this finding.

guarantee appears to boost the overall college enrollment and flagship enrollment among top decile graduates from typical Texas public high schools with average shares of economically disadvantaged students. Figure 9 shows large disjuncture at the cutoff point for flagship enrollment. That nearly half of Texas public high school seniors attend such “typical” schools attests to the profound impact of the top 10% law in raising college-going in the state, and particularly in equalizing access to the flagships for students across the state.

Figure 9 About Here

Finally, inclusion of the control variables rarely leads to substantive changes in coefficient estimates. Overall, both the magnitude and the significance of the estimates are sustained when control variables for students’ socioeconomic status are modeled. Only in three instances is statistical significance lost with the inclusion of the control variables; however, in each of these instances, the magnitude of the point estimates is sustained despite the larger standard errors. The similarity of the estimates with and without the controls suggests that the top 10% status indicator does not capture discontinuity in background characteristics at the cut-point.

Sensitivity Test to the Cutoff Point

All the analyses reported above test whether there is a statistically significant discontinuity in college enrollment at the actual 10 percentile class rank cutpoint, as specified under the Texas top 10% law. Following the example given by Kane (2003) in estimating the impact of the financial aid on college-going, we also test whether the actual percentile class rank cutpoint fits the data better than other nearby thresholds in order to rule out spurious relationships due to misspecification. For this analysis we re-

estimate the probit specifications for the full sample using a range of alternative cutpoints in the percentile class rank distribution, between 1 and 20 at single percentile intervals. Figure 10 reports the differences in the log likelihood for each specification relative to maximum log likelihood across all specifications. In general, the log likelihoods indicate that the data strongly conform to a cutoff point in the neighborhood of the 10th percentile of the class rank distribution whenever a significant program effect is obtained. For the first outcome variable, college enrollment, there is a clear “spike” in the log likelihood at the 10th percentile class rank, which corresponds with the eligible cutoff point implied by the top 10% law.

Figure 10 About Here

The maximum log likelihood occurs at the 2nd percentile class rank for enrollment in a 4-year institution (among college-goers), but the log likelihoods are very close to the maximum at the 3rd to 5th percentile class rank and then spike again at the 12th percentile class rank. This ambiguity of the best fit cutoff point partly is due to the final model specification used. As noted earlier, the estimates of the impact of the law are quite large and statistically significant for the 1% level of confidence for specifications with the 3rd and lower order polynomial and interactions.¹³ Thus, our estimates may understate the program effect, but we do not risk obtaining a pseudo-effect due to under-specification (Trochim, 2006). Our selection of this functional form specification was guided by Trochim’s (2006) logic as well as the substantive questions at hand. Although the specifications with higher order and additional interaction terms produce a slightly better fit to the data, results are difficult to interpret. Therefore we sacrifice slightly on precision

¹³ The estimates are actually larger in specifications with the 3rd order polynomial and interactions and with the 2nd order polynomial and interactions than that in the final specification, which includes a 2nd order polynomial and a linear interaction term.

to maintain interpretability. Nevertheless, we also re-estimated the probit specifications using the alternative percentile class rank cutoff points for two higher order specifications – the 3rd order polynomial with interactions and the 2nd order polynomial with interactions. These results also show a clear “spike” in the log likelihood in the neighborhood of the 10th percentile class rank, but the most preferred cutoff point is actually at the 8th percentile.

For in-state enrollment among 4-year college-goers, the “spike” in the log likelihood occurs at the 12th percentile class rank and the log likelihood is very close to the maximum at the 10th percentile class rank. This result is plausible substantively because many of the 4-year public institutions have relatively open admissions hence the top 10% law is unlikely to exclude many students who ranked below the second decile. However, the differences in the log likelihood for each specification relative to the maximum log likelihood across all specifications are less than 1.92, and mostly less than 1.35, implying that the 95 percent confidence interval would include all alternative cutoff points between 1 and 20. This test further affirms that the lack of statistical significance results because most of Texas high school seniors remain in state for their 4-year college education.

Finally, for flagship enrollment, the ‘spike’ occurs at the 6th percentile class rank, and the log likelihood is very close to the maximum at the 4th percentile class rank, at which points the actual flagship enrollment rates dips for reasons that are not obvious, except that rank-eligible students may attend institutions that are closer to their residence. However, the log likelihoods in the neighborhood of the 10th percentile class rank are

close to the minimum, which confirms the insignificant point estimate at the cutoff point of the 10th percentile class rank.

Conclusions

As the first and boldest percent plan, the Texas case deserves a fair hearing using scientific rather than anecdotal evidence to appreciate not only the actual, but also the potential changes in access to selective college campuses in the context of rapid demographic diversification of the school-age population. This study provides such evidence and directly assesses the impact of the Texas top 10% law on college enrollment decisions of students eligible for the admission guarantee by using precise class rank information verified from high school transcripts and applying regression discontinuity techniques to establish causal impacts.

Based on comparisons in college enrollment outcomes between students at the cutoff point and those immediately below, we identify four major consequences of the top 10% law. First, rank-eligible seniors are more likely to enroll in college, and also more likely to enroll in a 4-year institution, although the boosting effect on 4-year enrollment diminishes for those close to the cutoff point. Second, while the top 10% law boosts 4-year college enrollment among white students, it also increases minority students' college enrollment overall and at 4-year institutions as well. Third, college decisions of top decile graduates from predominately white or integrated high schools were not affected by the top 10% law, but rank-eligible students who graduated from minority schools are more likely to enroll in college, to enroll in a 4-year institution, and to enroll in one of the public flagships. These results are striking in their consistency both

with the design and intent of the law, namely to restore diversity at the public flagships by capitalizing on high school segregation and to increase college access to a broader spectrum of the Texas population. Finally, the top 10% law raises college enrollment and 4-year enrollment among top 10% students who graduate from Longhorn/Century high schools, although the boosting effect in 4-year enrollment disappears for those close to the cutoff point. UT and TAMU target rank-eligible graduates from these high schools for outreach programs and scholarship offers, yet we fail to find evidence that the top 10% law boosts flagship enrollment their top 10% decile students. However, this DOES NOT mean that the outreach efforts and targeted scholarship programs are inconsequential for flagship enrollment among students who are eligible for the admission guarantee.

As a final note, we emphasize that our application of the RD approach evaluates whether the Texas top 10% law has significant boosting effects on college enrollment of rank-eligible students. We do not compare its effectiveness in recruiting black and Hispanic students with race-sensitive admission policies. That we find significant boosting effects on overall college enrollment and matriculation in 4-year, and marginally significant effects on flagships enrollment among minority students does not necessarily mean that the top 10% law is an effective alternative to affirmative action. Other studies have demonstrated that **it is not** an effective alternative to recruit black and Hispanic students (Kain et al., 2005, Long and Tienda, 2006).

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Table 1. Variable Means by Top 10% Status

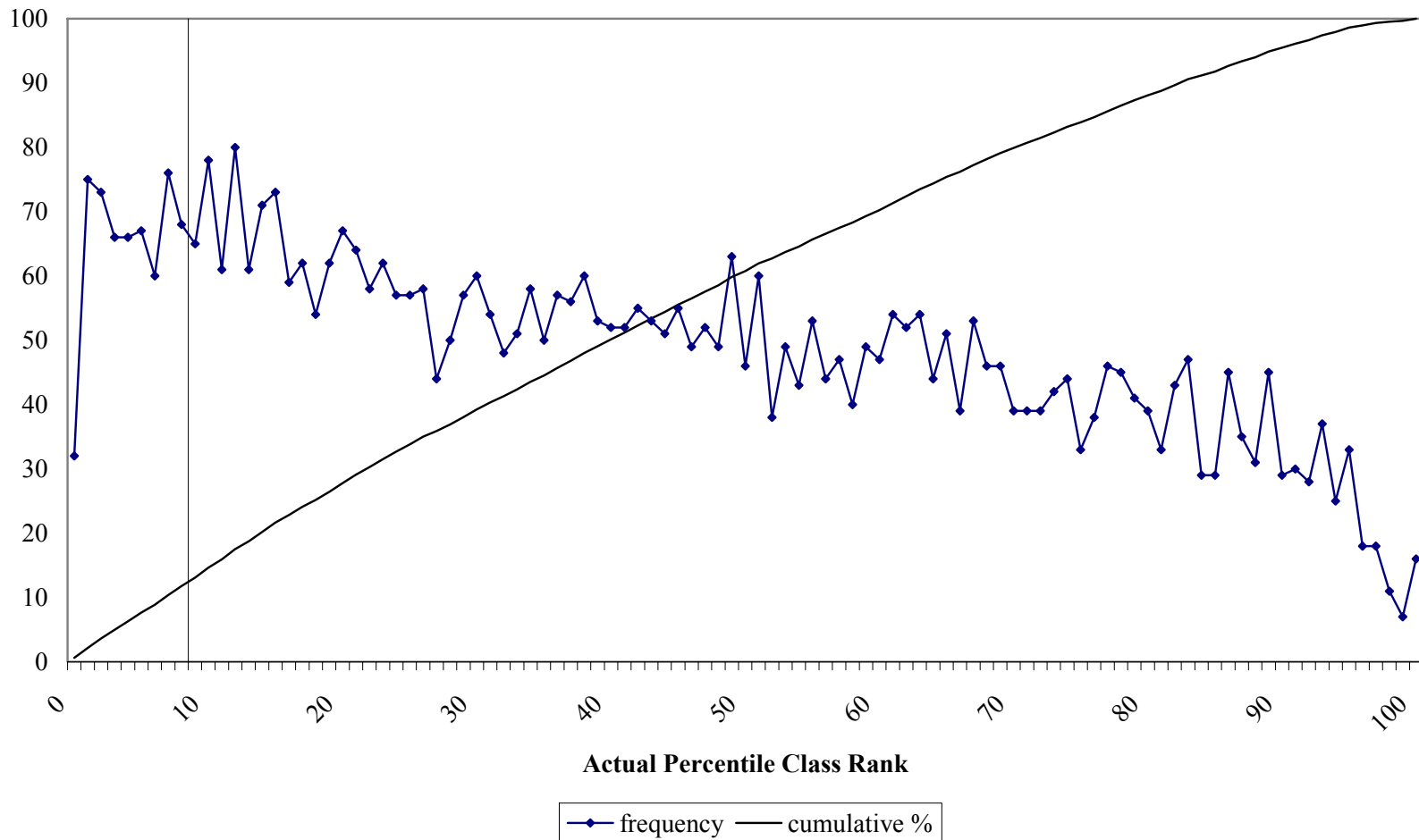
	Full Range		10% Interval		6% Interval	
	Top 10%	20-100%	6-10%	11-15%	8-10%	11-13%
Outcome Variables						
Enrolled in College	0.94	0.71 ***	0.94	0.89 *	0.94	0.86
Enrolled 4-year among Enrollees	0.88	0.51 ***	0.86	0.76 ***	0.84	0.75 *
Enrolled TX 4-year among 4-year Enrollees	0.88	0.88	0.91	0.89	0.93	0.89
Enrollees	0.45	0.12 ***	0.43	0.31 **	0.42	0.34
Control Variables						
Race/Ethnicity						
White	0.45	0.37 ***	0.43	0.50	0.48	0.52
Black	0.11	0.19 ***	0.14	0.10	0.10	0.11
Hispanic	0.28	0.38 ***	0.29	0.30	0.28	0.29
Asian	0.15	0.05 ***	0.13	0.07 **	0.12	0.06
Other/Missing	0.01	0.02	0.01	0.02	0.01	0.01
Parental Education						
Less Than High School	0.11	0.16 ***	0.11	0.17 *	0.09	0.16 *
High School	0.17	0.21 **	0.19	0.19	0.19	0.17
Some College	0.25	0.23	0.25	0.20	0.21	0.19
College and Higher	0.38	0.21 ***	0.33	0.34	0.36	0.35
Don't Know/Missing	0.09	0.19 ***	0.12	0.11	0.15	0.12
Home Ownership						
Own	0.82	0.70 ***	0.80	0.74	0.79	0.74
Rent	0.11	0.15 **	0.12	0.14	0.13	0.14
Don't Know/Missing	0.07	0.15 ***	0.08	0.12	0.09	0.11
First Thought About College Going						
Always	0.78	0.54 ***	0.73	0.74	0.74	0.74
Middle High School	0.10	0.12	0.13	0.10	0.13	0.1
High School	0.07	0.19 ***	0.08	0.11	0.07	0.09
Don't Know/Missing	0.05	0.15 ***	0.07	0.06	0.06	0.06
N	725	4214	347	345	211	201

Source: THEOP Wave 1 & 2 Senior Surveys.

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

Notes: The case numbers refer to college enrollment choice, the numbers are smaller for 4-year, in-state and flagship enrollment choices.

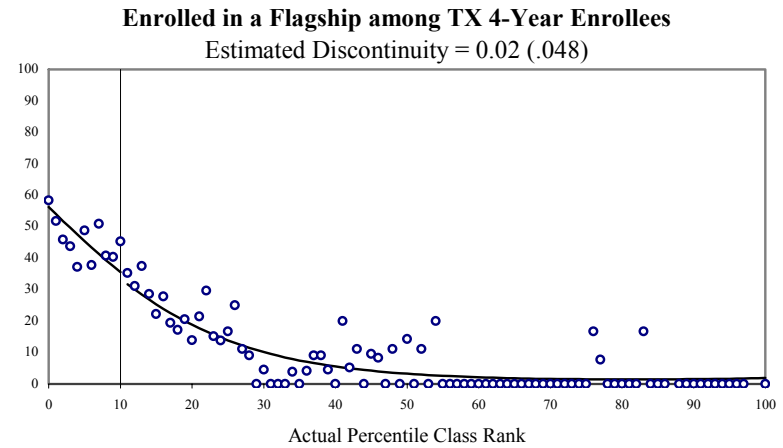
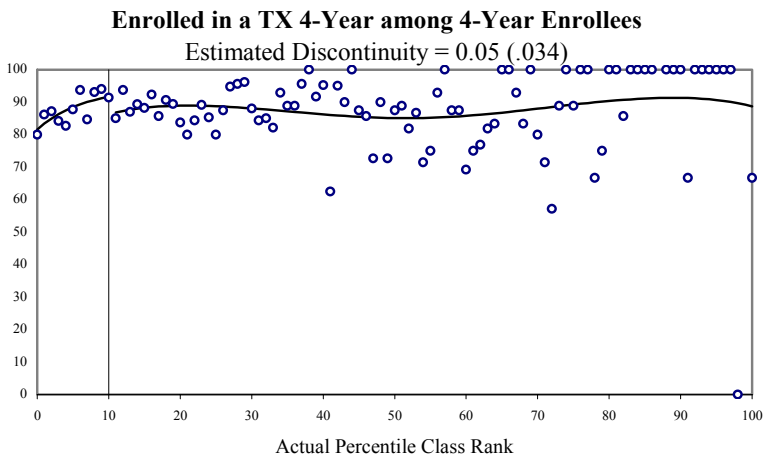
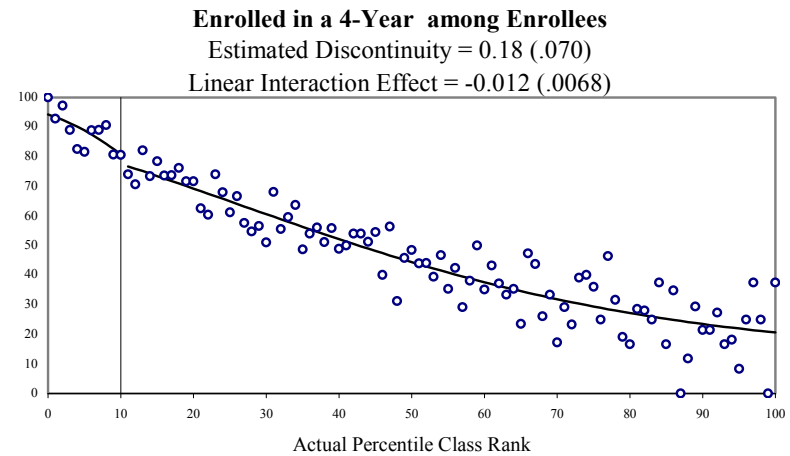
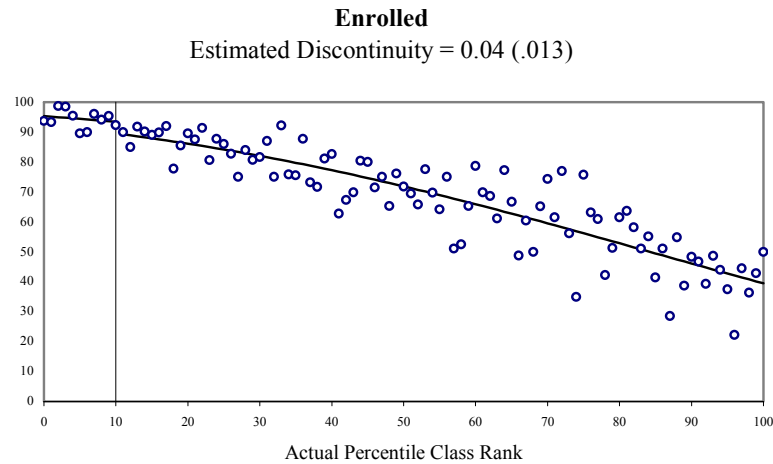
Figure 1. Distribution of High School Seniors by Actual Class Rank Percentile



Source: THEOP Wave 1 & 2 Senior Surveys.

Figure 2: Probability of College Enrollment by Actual Percentile Class Rank: All Seniors

○: actual; —: predicted



Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Table 2. Probit Regression Discontinuity Estimates of the Impact of the Top 10% Law on College Enrollment Texas Public High School Seniors in 2002
(Marginal Effect, S.E. in parenthesis)

Outcome	Marginal Effects of Top10% Status	
Enrolled in College n=4939	0.04 ** (.013)	0.02 (.012)
Enrolled 4-year among Enrollees n=3667	0.18 *** (.070)	0.16 ** (.069)
linear interaction term	-.012 * (.0068)	-.010 (.0067)
Enrolled TX 4-year among 4-year Enrollees n=2117	0.05 (.034)	0.05 (.032)
Enrolled TX Flagships among TX 4-year Enrollees n=1856	0.02 (.048)	0.03 (.048)
Controls Included?	N	Y

Source: THEOP Wave 1 & 2 Senior Surveys.

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

Notes: Each cell represents the estimated discontinuity in the outcome, defined as the marginal effect of being in the top decile obtained from the following equations, estimated with a probit specification, calculated at the sample means of those at the cutoff point.

$$\text{Enrolled} = \text{rank} + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon;$$

$$\text{Enrolled 4-year} = \text{rank} + \text{rank}^2 + \alpha_1 \cdot \text{Top10\%} + \alpha_2 \cdot (\text{Top10\%} \cdot \text{rank}) + \beta Z + \varepsilon;$$

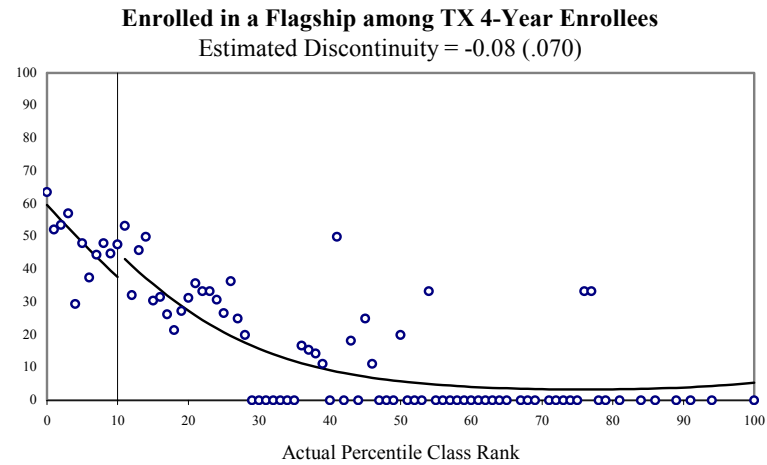
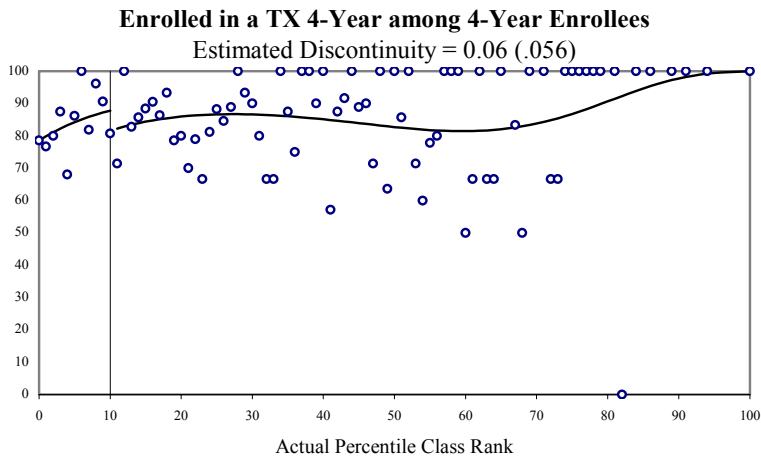
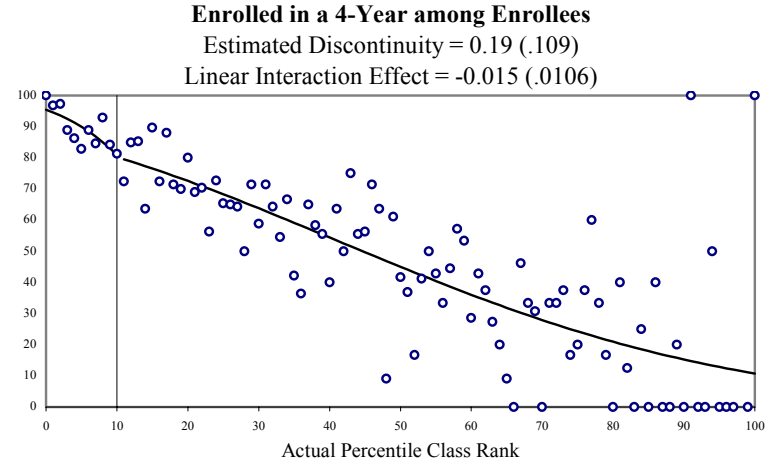
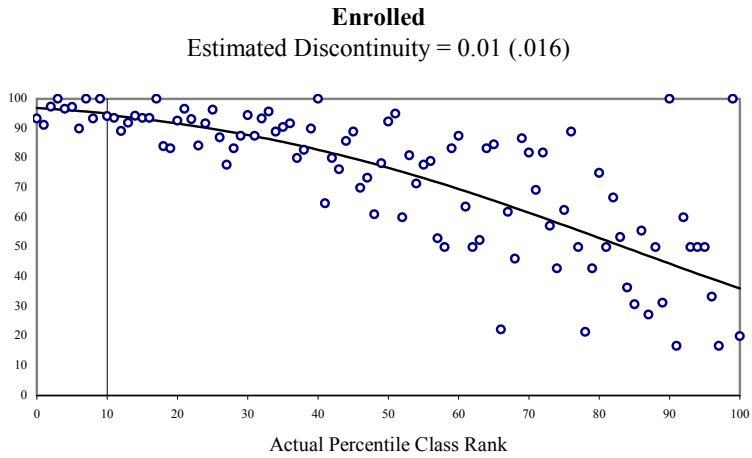
$$\text{Enrolled TX 4-year} = \text{rank} + \text{rank}^2 + \text{rank}^3 + \text{rank}^4 + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon;$$

$$\text{Enrolled TX Flagships} = \text{rank} + \text{rank}^2 + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon;$$

where Z is a control vector, including family SES variables (parent education and home ownership) and student's college disposition (grade level when student first considered college). The baseline models exclude the control variables.

Figure 3: Probability of College Enrollment by Actual Percentile Class Rank: White

○: actual; —: predicted

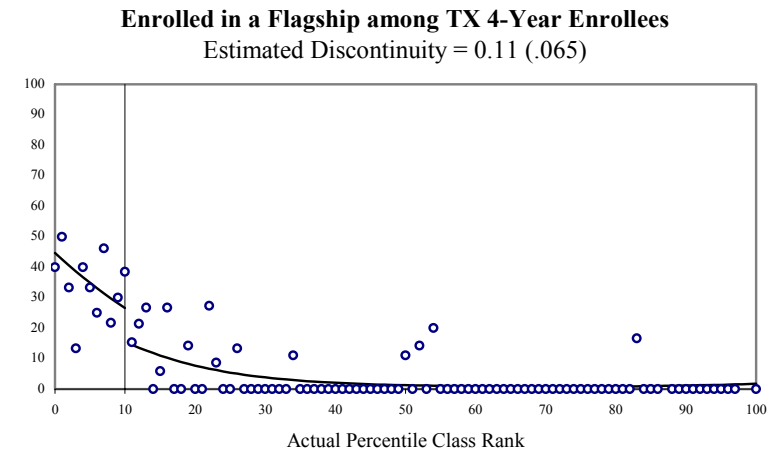
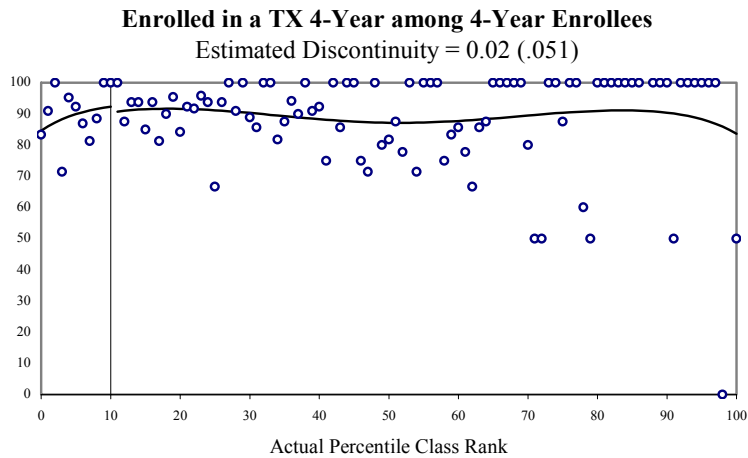
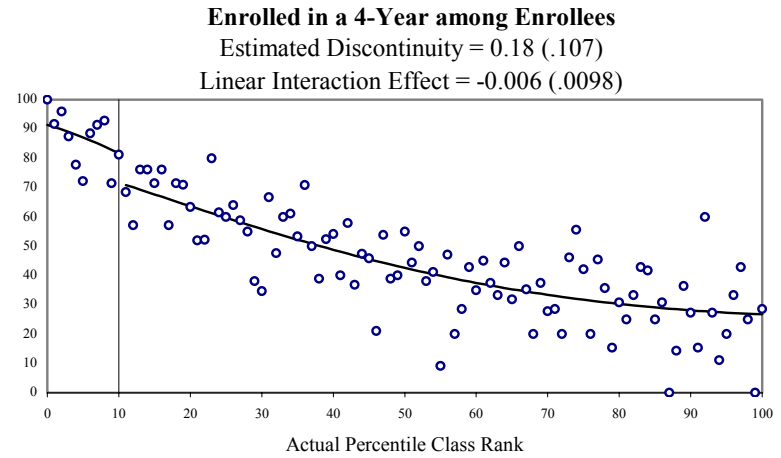
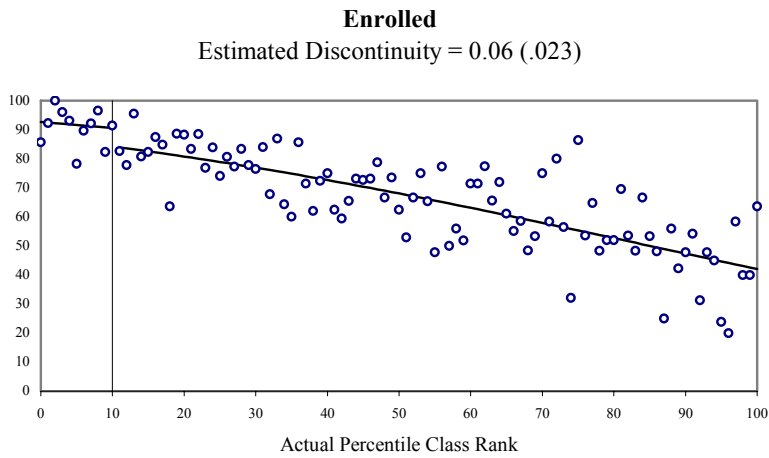


Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Figure 4: Probability of College Enrollment by Actual Percentile Class Rank: Black and Hispanic

○: actual; —: predicted



Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Table 3. Probit Regression Discontinuity Estimates of the Impact of the Top 10% Law on College Enrollment, Texas Public High School Seniors in 2002 by Race/Ethnicity
(Marginal Effect, S.E. in parenthesis)

Outcome	Marginal Effects of Top10% Status									
	White		Black		Hispanic		Asian		Black&Hispanic	
Enrolled in College	0.01 (.016) n=1899	-0.01 (.013)	0.03 (.034) n=860	0.03 (.023)	0.08 ** (.029) n=1804	0.06 * (.030)	0.08 (.041) n=292	0.03 (.030)	0.06 ** (.023) n=2664	0.05 * (.022)
Enrolled 4-year among Enrollees	0.19 * (.109)	0.18 * (.110)	0.36 (.307)	0.38 (.328)	0.16 (.117)	0.14 (.116)	0.24 (.233)	0.09 (.194)	0.18 * (.107)	0.17 * (.108)
linear interaction term	-0.015 (.0106) n=1525	-0.014 (.0104)	-0.036 (.0358) n=658	-0.037 (.0365)	-0.001 (.0104) n=1175	0.000 (.0101)	-0.022 (.0207) n=248	-0.007 (.0153)	-0.006 (.0098) n=1833	-0.006 (.0097)
Enrolled TX 4-year among 4-year	0.06 (.056) n=938	0.06 (.055)	0.05 (.107) n=397	0.05 (.114)	0.03 (.062) n=559	0.02 (.061)	0.06 (.072) n=182	0.09 (.114)	0.02 (.051) n=956	0.02 (.052)
Enrolled TX Flagships among TX 4-year Enrollees	-0.08 (.070) n=794	-0.08 (.072)	0.11 (.118) n=336	0.10 (.143)	0.14 (.084) n=552	0.12 (.084)	0.25 (.165) n=169	0.20 (.182)	0.11 (.065) n=858	0.10 (.067)
Controls Included?	N	Y	N	Y	N	Y	N	Y	N	Y

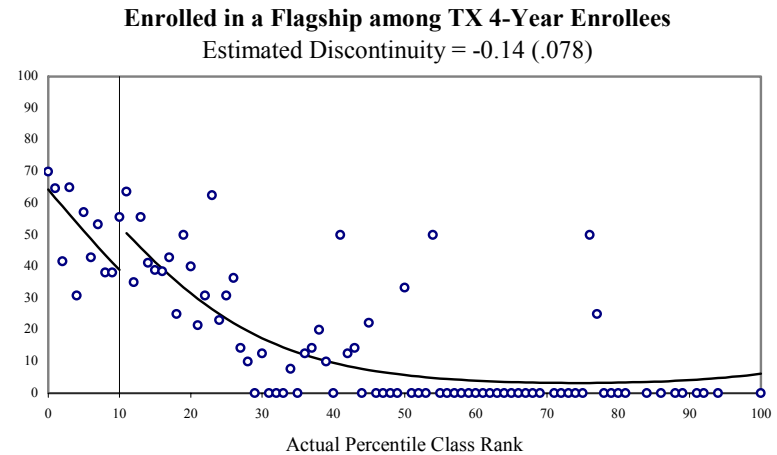
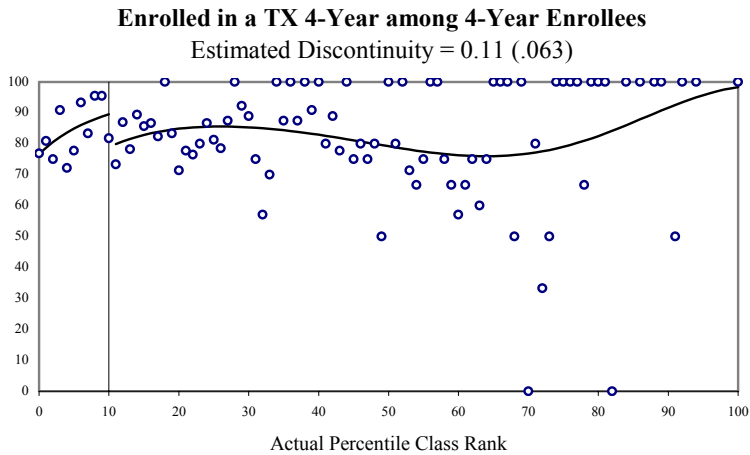
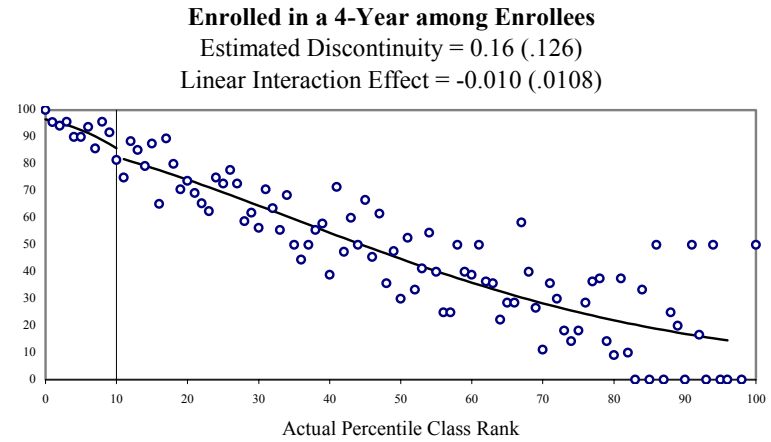
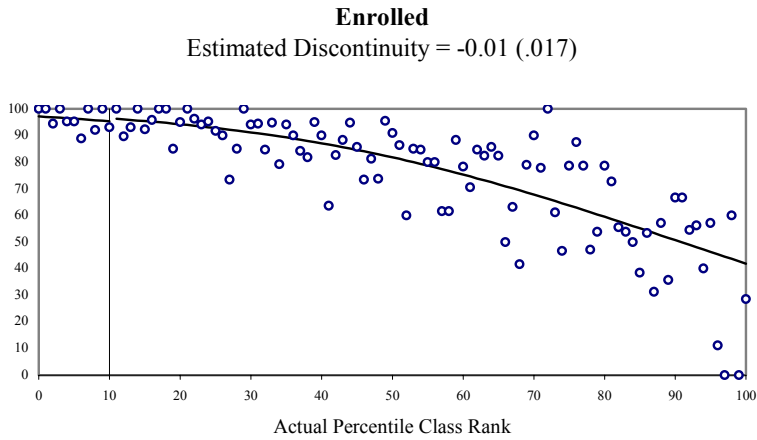
Source: THEOP Wave 1 & 2 Senior Surveys.

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

Notes: Each cell represents the estimated discontinuity in the outcome. It is the marginal effect of being in the top decile obtained from probit regressions. See notes to Table2 for additional details.

Figure 5: Probability of College Enrollment by Actual Percentile Class Rank: Predominately and Majority White High Schools

○: actual; —: predicted

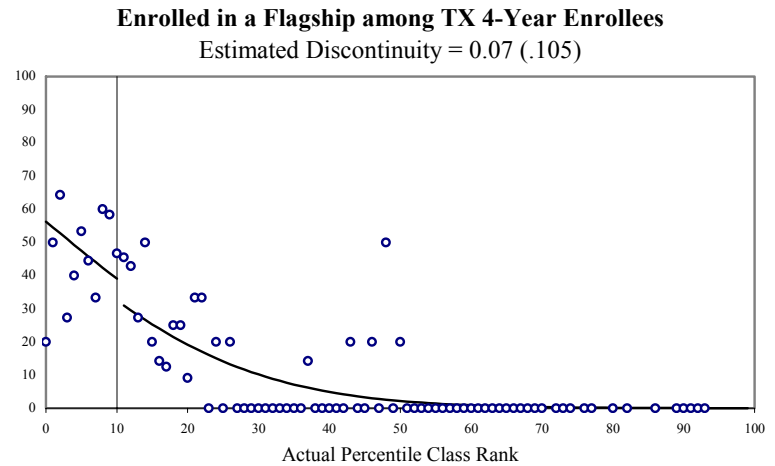
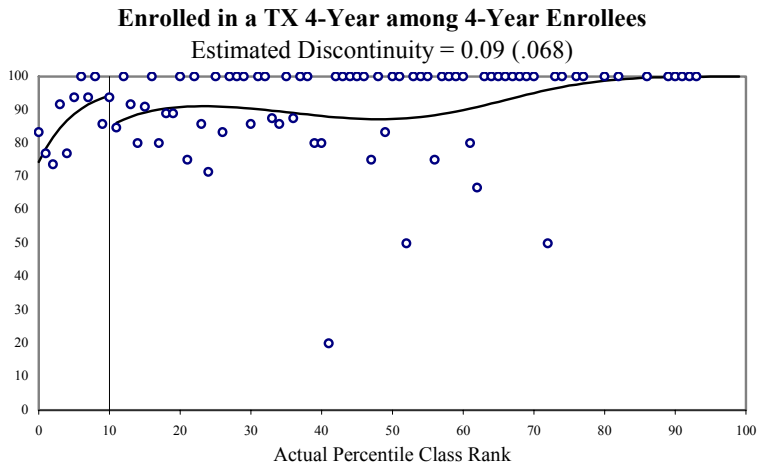
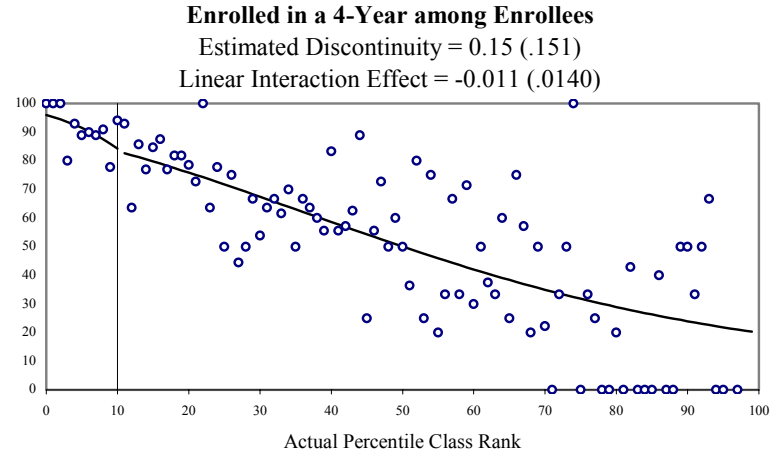
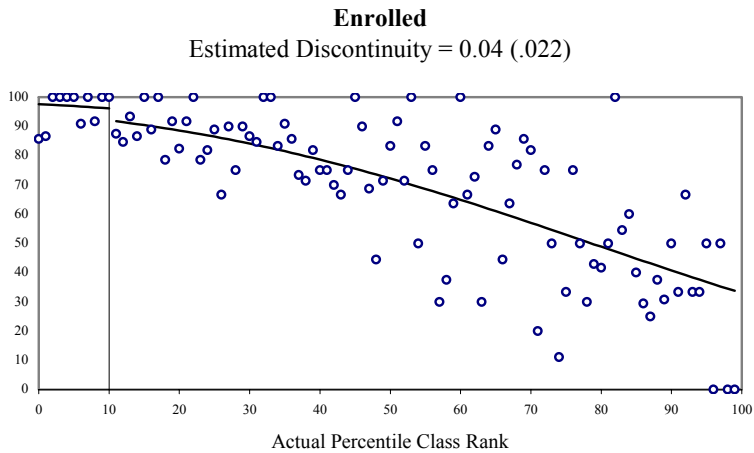


Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Figure 6: Probability of College Enrollment by Actual Percentile Class Rank: Integrated High Schools

○: actual; —: predicted

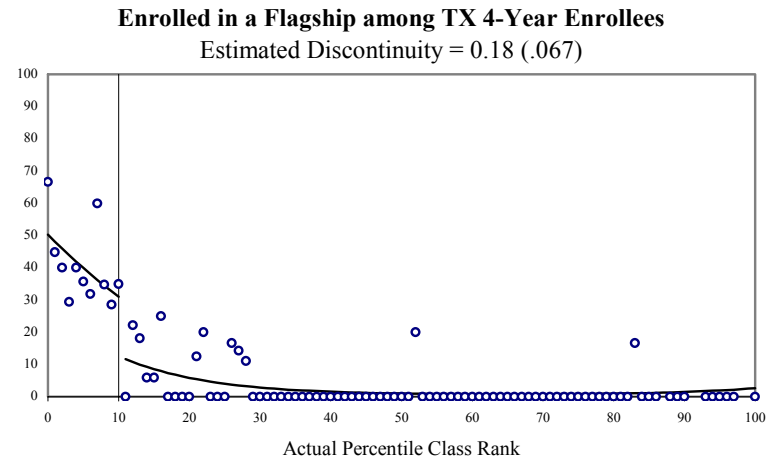
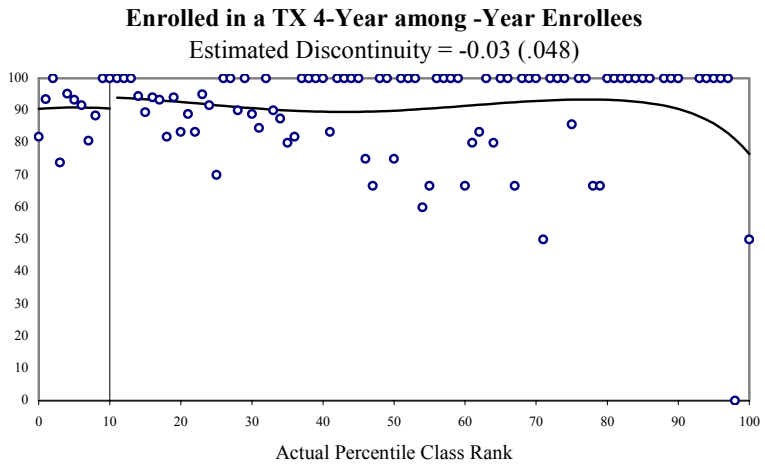
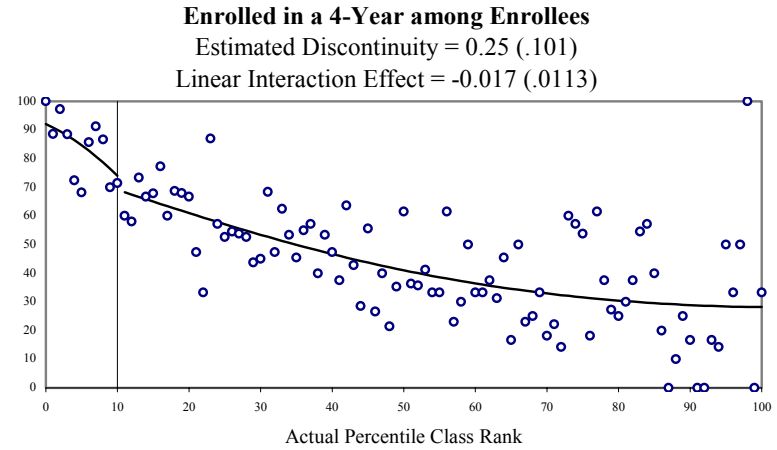
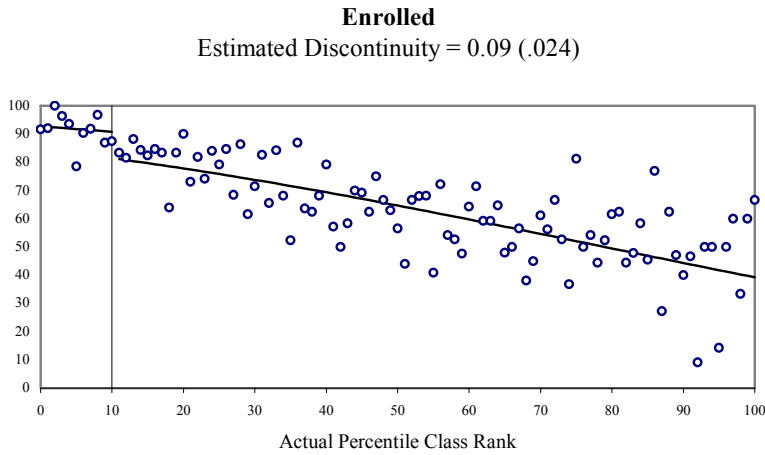


Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Figure 7: Probability of College Enrollment by Actual Percentile Class Rank: Predominately and Majority Minority High Scho

○: actual; —: predicted



Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Table 4. Probit Regression Discontinuity Estimates of the Impact of the Top 10% Law on College Enrollment Texas Public High School Seniors in 2002 by High School Race/Ethnicity Composition
(Marginal Effect, S.E. in parenthesis)

Outcome	Marginal Effects of Top10% Status									
	Predominately White		Majority White		Integrated		Majority Minority		Predominately Minority	
Enrolled in College	-0.02 (.031) n=543	-0.02 (.034)	-0.01 (.020) n=1161	-0.01 (.013)	0.04 (.022) n=1044	0.03 (.019)	0.15 * (.058) n=353	0.17 * (.071)	0.08 ** (.026) n=1838	0.06 * (.027)
Enrolled 4-year among Enrollees	0.26 (.329) n=448	0.29 (.345)	0.13 (.136) n=942	0.08 (.116)	0.15 (.151) n=778	0.12 (.146)	0.36 (.153) n=222	0.35 (.135)	0.22 * (.114) n=1277	0.17 (.114)
linear interaction term	-0.008 (.0202) n=448	-0.009 (.0203)	-0.010 (.0128) n=942	-0.006 (.0107)	-0.011 (.0140) n=778	-0.010 (.0137)	-0.033 (.0290) n=222	-0.036 (.0295)	-0.014 (.0119) n=1277	-0.011 (.0118)
Enrolled TX 4-year among 4-year	0.20 (.118) n=252	0.22 (.131)	0.07 (.076) n=559	0.08 (.079)	0.09 (.068) n=494	0.08 (.064)	-0.24 (.175) n=101	-0.32 (.260)	-0.01 (.048) n=711	-0.01 (.044)
Enrolled TX Flagships among TX 4-year Enrollees	-0.30 (.150) n=213	-0.30 (.165)	-0.07 (.092) n=460	-0.08 (.098)	0.07 (.105) n=441	0.12 (.115)	0.17 (.208) n=79	0.29 (.330)	0.19 ** (.072) n=663	0.17 ** (.064)
Controls Included?	N	Y	N	Y	N	Y	N	Y	N	Y

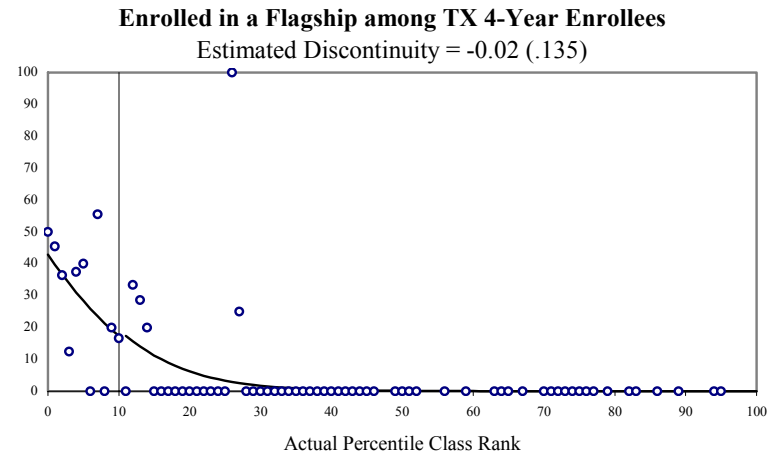
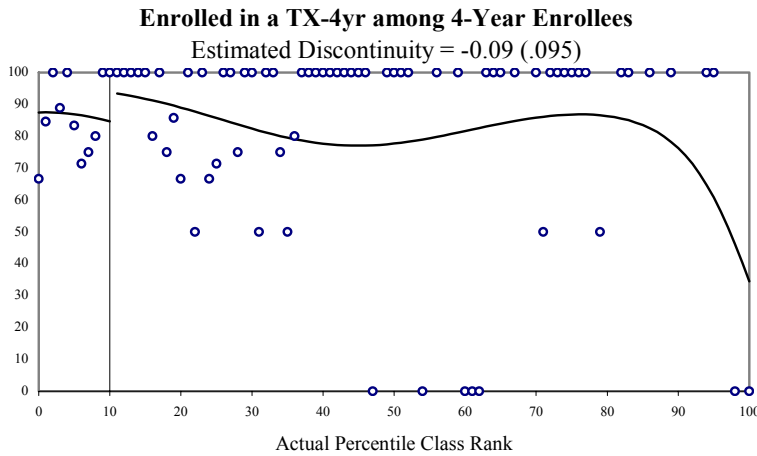
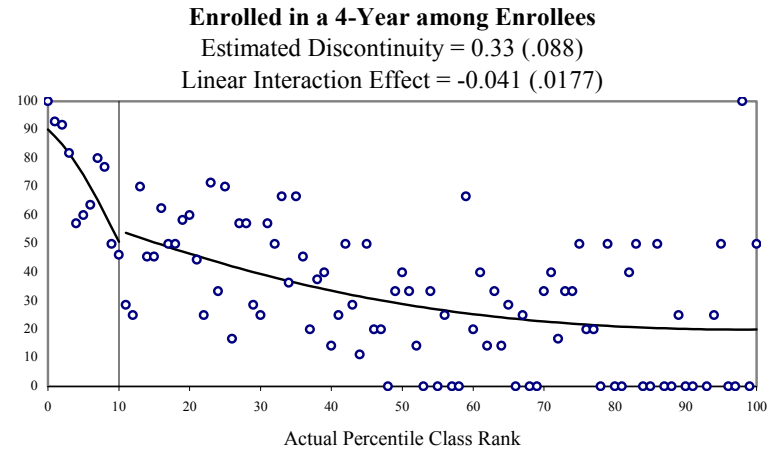
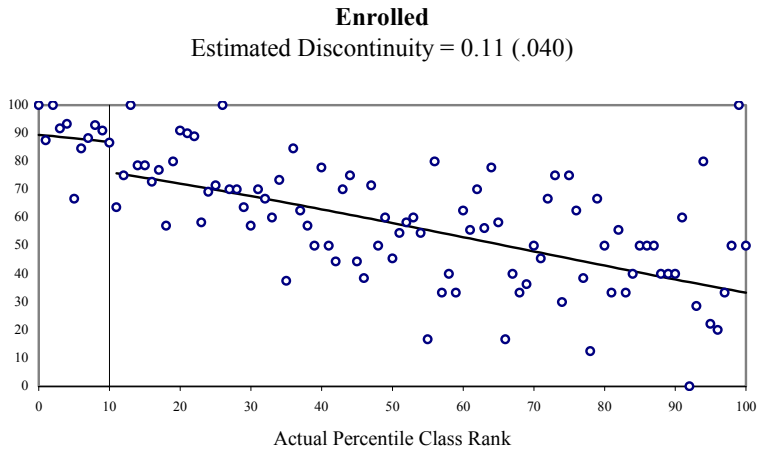
Source: THEOP Wave 1 & 2 Senior Surveys.

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

Notes: Each cell represents the estimated discontinuity in the outcome. It is the marginal effect of being in the top decile obtained from probit Regressions. See notes to Table2 for additional details.

Figure 8: Probability of College Enrollment by Actual Percentile Class Rank: Longhorn/Century High Schools

○: actual; —: predicted

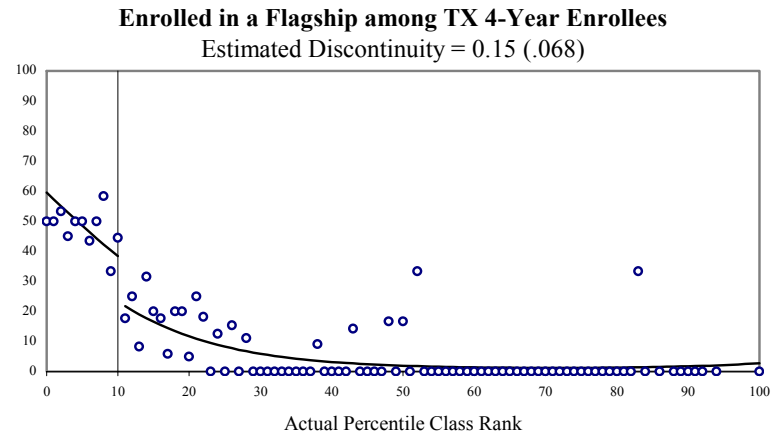
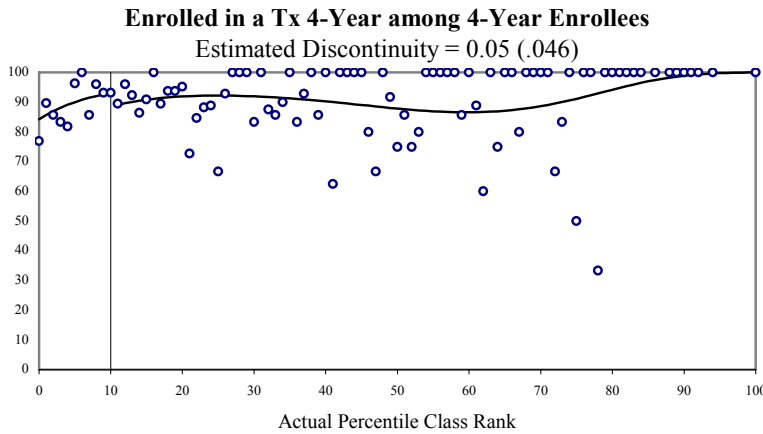
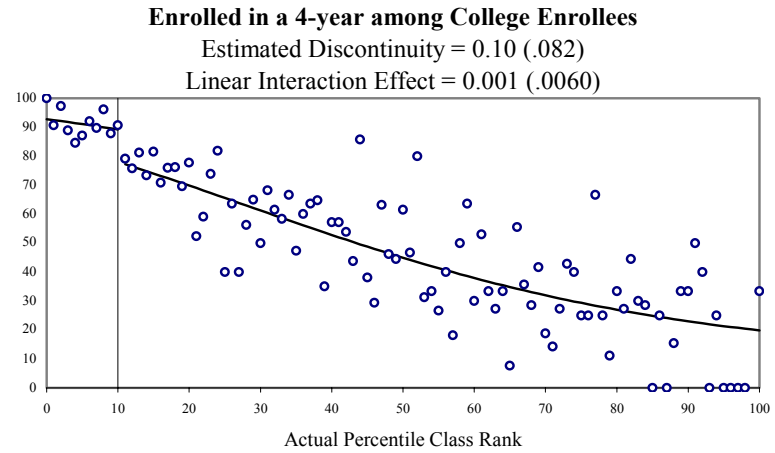
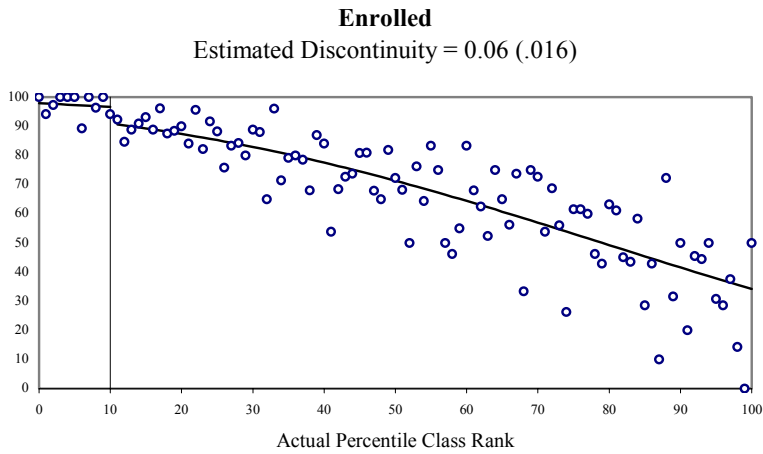


Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Figure 9: Probability of College Enrollment by Actual Percentile Class Rank: Typical High Schools

○: actual; —: predicted



Source: THEOP Wave 1 & 2 Senior Surveys.

Notes: The predicted probabilities are from baseline probit regressions. See notes to Table 2 for further details.

Table 5. Probit Regression Discontinuity Estimates of the Impact of the Top 10% Law on College Enrollment Texas Public High School Seniors in 2002 by High School Type
(Marginal Effect, S.E. in parenthesis)

Outcome	Marginal Effects of Top10% Status									
	Feeder		Affluent		Typical		Poor		Longhorn/Century	
Enrolled in College	-- ^a	-- ^a	-0.02	-0.02	0.06 **	0.04 **	0.03	-0.02	0.11 **	0.10 *
			(.021)	(.017)	(.016)	(.013)	(.055)	(.060)	(.040)	(.046)
	n=256		n=1020		n=2149		n=511		n=969	
Enrolled 4-year among Enrollees	-0.05	-0.02	0.17	0.18	0.10	0.07	0.50	0.47	0.33 **	0.29 *
	(.049)	(.031)	(.165)	(.170)	(.082)	(.073)	(.249)	(.308)	(.088)	(.088)
linear interaction term	0.005	0.003	-0.013	-0.013	0.001	0.002	-0.046	-0.038	-0.041 *	-0.036 *
	(.0088)	(.0038)	(.0146)	(.0147)	(.0060)	(.0056)	(.0443)	(.0427)	(.0177)	(.0176)
	n=271		n=850		n=1588		n=353		n=605	
Enrolled TX 4-year among 4-year	0.15	0.12	0.08	0.06	0.05	0.05	0.08	0.03	-0.09	-0.14
	(.131)	(.128)	(.086)	(.083)	(.046)	(.046)	(.096)	(.083)	(.095)	(.114)
	n=208		n=496		n=944		n=213		n=256	
Enrolled TX Flagships among TX 4-year Enrollees	-0.14	-0.22	-0.10	0.12	0.15 *	0.16 *	-0.14	-0.09	-0.02	0.04
	(.150)	(.171)	(.106)	(.110)	(.068)	(.065)	(.150)	(.147)	(.135)	(.136)
	n=170		n=409		n=853		n=206		n=218	
Controls Included?	N	Y	N	Y	N	Y	N	Y	N	Y

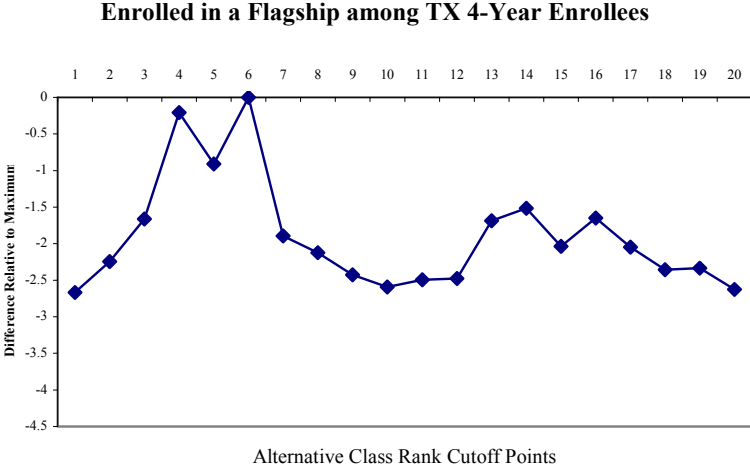
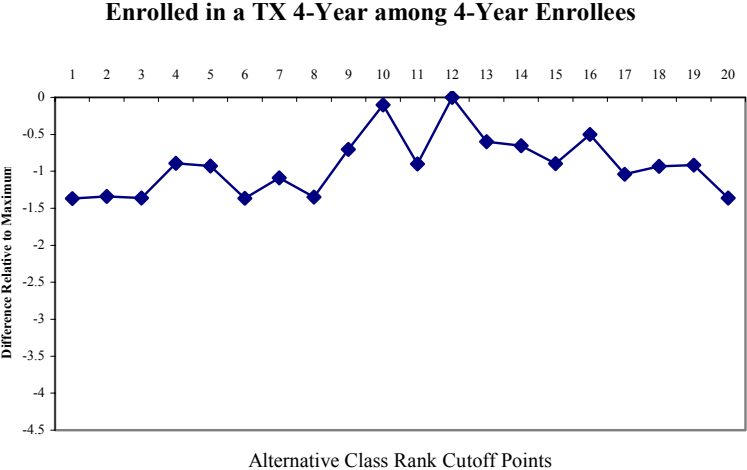
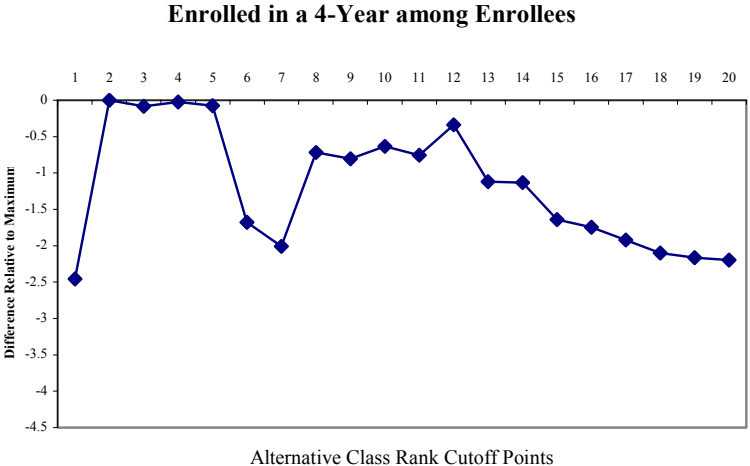
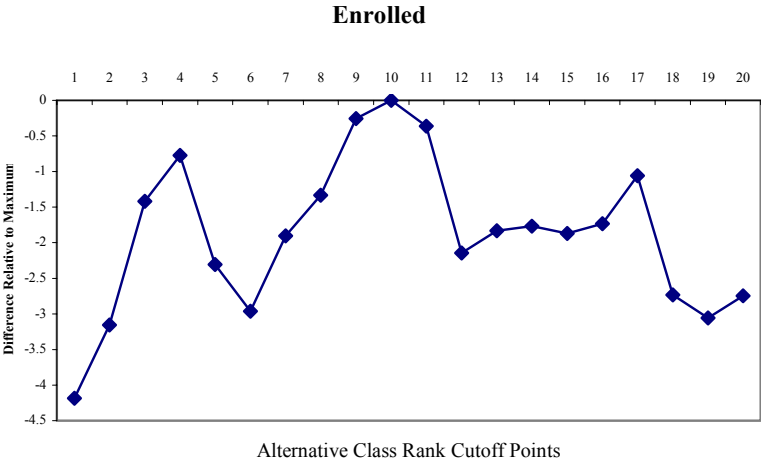
Source: THEOP Wave 1 & 2 Senior Surveys.

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

Notes: Each cell represents the estimated discontinuity in the outcome. It is the marginal effect of being in the top decile obtained from probit regressions. See notes to Table2 for additional details.

a: Not estimated because all top 10% students enrolled in college.

Figure 10: Evaluating the Log Likelihood Using Alternative Class Rank Cutoff Points



Source: THEOP Wave 1 & 2 Senior Surveys.

Appendix 1. Changes in Coefficient for top 10% status and Pseudo R-Sq in Varying Polynomial Specification (s.e. in parenthesis)

Outcome	Polynomial in Class Rank	Polynomial Specification								Final Specification ^a
		4		3		2		1		
Enrolled in College n=4939	Top 10%					0.28 (.251)	0.24 (.110)	0.28 (.164)	0.25 (.089)	0.25 (.089)
	Pseudo R-Sq					0.1105	0.1105	0.1105	0.1105	0.1105
Enrolled 4-year among College Enrollees n=3667	Top 10%			1.3 (.440)	0.17 (.128)	0.78 (.254)	0.27 (.099)	0.73 (.148)	0.43 (.078)	0.54 (.171)
	Pseudo R-Sq			0.1435	0.1416	0.1425	0.1413	0.1412	.1400	0.1421
Enrolled TX 4-year among 4-year Enrollees n=2117	Top 10%	0.34 (.636)	0.29 (.184)	-0.19 (.380)	0.19 (.173)	-0.35 (.239)	-0.03 (.136)	-0.23 (.148)	0.01 (.100)	0.29 (.184)
	Pseudo R-Sq	0.0060	0.0052	0.0044	0.0027	0.0042	0.0001	0.0032	0.0000	0.0052
Enrolled TX Flagships among TX 4-year n=1856	Top 10%	-0.22 (.729)	0.13 (.150)	-0.39 (.413)	0.11 (.149)	-0.15 (.236)	0.06 (.130)	0.22 (.147)	0.29 (.101)	0.06 (.130)
	Pseudo R-Sq	0.1869	0.1851	0.1868	0.1834	0.1859	0.1831	0.1794	0.1792	0.1831
Full Interactions Included		Y	N	Y	N	Y	N	Y	N	

Source: THEOP Wave 1 & 2 Senior Surveys.

a: The final specifications are the following:

$$\text{Enrolled} = \text{rank} + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon;$$

$$\text{Enrolled 4-year} = \text{rank} + \text{rank}^2 + \alpha_1 \cdot \text{Top10\%} + \alpha_2 \cdot (\text{Top10\%} * \text{rank}) + \beta Z + \varepsilon;$$

$$\text{Enrolled TX 4-year} = \text{rank} + \text{rank}^2 + \text{rank}^3 + \text{rank}^4 + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon;$$

$$\text{Enrolled TX Flagships} = \text{rank} + \text{rank}^2 + \alpha_1 \cdot \text{Top10\%} + \beta Z + \varepsilon;$$

where Z is a control vector, including family SES variables (parent education and home ownership) and student's college disposition (grade level when student first considered college). The baseline models exclude the control variables.