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ABSTRACT

The Effects of Academic Probation on College Success: Regression Discontinuity Evidence from Four Texas Universities*

While nearly all colleges and universities in the United States use academic probation as a means to signal to students a need to improve performance, very little is known about the use of this designation and the programs that accompany it on college success. This paper uses a regression discontinuity approach to estimate the effects of these programs at four universities of varying selectivity in Texas. Results suggest that academic probation status following the first semester of college may serve as a short term "wake up call" to some students, in that second semester performance is improved. However, our findings also suggest that this short term boost in performance fades out over time and students who are on academic probation following their first semesters of college do not have higher rates of persistence or graduation. We also find important differential responses to academic probation based on pre-determined student characteristics as well as high school of origin. However none of the heterogeneous effects are consistent across universities, limiting the application of simple models of education standards.

JEL Classification: J24, I21

Keywords: academic probation, regression discontinuity, higher education

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Introduction

Nearly all colleges and universities in the United States currently use academic probation as a way to signal students a need to improve performance or else discontinue their education at the school. The basic structure of these programs is typically a minimum grade point average (GPA) requirement, either based on current or cumulative (or both) academic performance. Universities often differ on what set of services or punishments is offered to students placed on probation: some universities place restrictions on participation in extracurricular activities and course work hours while other universities provide additional help with coursework to these "at risk" students.

This paper uses the strict GPA cutoff in order to implement a regression discontinuity (RD) estimation design to estimate the effects of these policies and also examines the potential heterogeneity of effects of academic probation status across subgroups of students as well as different universities. While there are many studies in the literature that compare students who are on academic probation with students who are not, causal estimates are rare. In fact, the only paper that examines causal effects of academic probation focuses on a single Canadian university (Lindo et al. 2010), who suggest that a relatively simple model fit their data quite well. Our paper is able to broaden the scope of this research question by examining the context of the United States higher education system as well as examining universities of varying selectivity and academic probation regimes to investigate whether a simple model can be extended to this broader context.

Overall, this paper finds short term positive effects of academic probation on outcomes in the semester following the designation. However, these effects appear to fade out quickly over time, resulting in no differences in graduation rates or later term college persistence. While we find considerable heterogeneity in the effects of academic probation status, diverging from the results from Lindo et al. (2010), we do not find any consistent patterns across universities, suggesting that a simple model would be inappropriate for our data. These findings further suggest the potential importance of local context and rules as well as the characteristics of the student population in understanding reactions to academic probation policies and point to the need for additional research using richer data before broad claims can be made about the effects of academic probation.

Background Literature

While there are large literatures that examine many university policies, such as financial aid, affirmative action, etc, relatively few studies have examined "negative incentives" or punishments in the university setting. Likely the most similar literature to that on academic probation is the emerging research that examines the effects of college remediation on college success. There are several similarities between academic probation and remediation that make this literature relevant. Both policies provide students information and both policies typically are used at the beginning of students' college careers.

Indeed, the regression discontinuity design has been used in several papers that evaluated the causal effects of remedial education on student achievement. In the context of elementary school students in the Chicago Public Schools, Jacob and Lefgren (2004) showed that summer school remediation increased academic achievement among third-graders. For college age students, Martorell and Mcfarlin (2007) present evidence that placement in college remediation courses have virtually no positive effect on students from Texas. Carlos Calcagno and Long (2008) find mixed evidence of remedial education for students in Florida community colleges—while remediation increases short term persistence and completed credit hours, it does not increase degree completion.

While this work might be suggestive when conceptualizing the potential effects (or non-effects) of academic probation, there are several differences in the policies that deserve attention. Importantly, college remediation, in principle, is meant to provide skills to students and promote college success. In contrast, many academic probation regimes are strictly punitive, in reducing extracurricular activities, allowable coursework, or even financial aid. Thus, the estimated effects of academic probation policies may substantially differ compared with remediation policies and also combine several "treatments" that vary by institution.

Even though most colleges and universities utilize academic probation policies, little is known about their effectiveness. Indeed, the research examining the effects of academic probation is almost entirely correlational, where the average college performance outcomes of individuals on academic probation are compared with the average outcomes of individuals who are not on probation (e.g. Scalice et al. 2000). This likely makes comparisons between students who are quite dissimilar along a range of observable and unobservable characteristics, such as family background and motivation.

Intuition of Empirical Design

In contrast to nearly all current literature that examines the effects of academic probation, this paper uses a regression discontinuity (RD) design, where individuals who earn GPAs slightly above or below the threshold for academic probation following the first semester of college are compared. Thus, this paper assumes that a good counterfactual for a student with a 1.99 GPA at the end of the fall of their freshman year of college is a student with a 2.01 GPA, who was not placed on academic probation. As both of these students would be predicted to perform relatively poorly in college, the estimates of the discontinuity indicate the "extra" effect of the policy, on top of the already predicted poor performance of each of these students. Thus, the estimated effect is the combination of being informed of performing poorly (i.e. the letter of academic probation from the school) as well as any services or restrictions provided by the school.

In order for this strategy to be valid, other student characteristics are required to be continuous through this threshold and students need to be unable to perfectly forecast their GPAs (i.e. no clumping just above the cutoff) (Lee and Lemeiux 2009, McCrary 2008). We show evidence that these conditions are satisfied below. We also examine the potential heterogeneity of effects by gender and other characteristics due to previous literature suggesting gender differences in response to performance standards[1] as well as direct evidence from Lindo et al. (2010) (henceforth LSO) suggesting such heterogeneous effects. While LSO was limited to examining the effects by gender, a rough measure of high school performance, and native language, we can expand the investigation by utilizing information on race, high school of origin, SAT test scores as well as across universities of differing levels of selectivity.

[1] See Dynarski (2005) and Angrist and Lavy (2002) for examples.

Consistent with the results of LSO as well as the conceptual model they outline, motivated from Benabou and Tirole's (2000) model of the effects of performance standards, we find heterogeneous impacts of academic probation. Academic probation status reduces the chances that some students return to school for their second year, although most complete their first year. For those students who return their second year, we find evidence of higher subsequent performance in the short term that fades out over time. We also document below that the effects of this program are heterogeneous by student-type and across schools. In fact, the high degree of heterogeneity by student observables and across schools makes the simple conceptual model outlined by LSO unable to fit our data.

Data

In this paper, we use longitudinal administrative data from four universities in Texas collected under the auspices of the Texas Higher Education Opportunity Project.[2] Two types of administrative records are available for each student. A baseline file includes background information of all students who applied in a given year, their admission decision, and conditional on acceptance, their enrollment decision. For matriculants, a term file records various measures of academic progress, notably persistence (measured by whether a student is still enrolled at the university in subsequent semesters), GPA, choice of major, and graduation status for each semester enrolled.

The data files analyzed includes every student who applied to the university from the early 1990's through approximately 2002. The administrative data also include a relatively rich set of academic and demographic variables for each college applicant, including SAT/ACT test scores, class rank, sex, and race/ethnicity. In addition to individual characteristics of all applicants, the administrative data contains high school and geographic identifiers, which permits measurement of the type of high school attended, including the poverty level of students, the history of enrollment patters from

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

the school to specific universities, and the size of students' high school peer groups upon entering college. Many of these variables have not been available in previous work.

While the basic structure of the files is the same across universities, we are also able to examine the potentially differential effects based on college selectivity and academic probation regime. The schools we focus on in this paper include the University of Texas-Austin (UT-Austin), Texas A&M (TAMU), Texas Tech University (Texas Tech), and UT-San Antonio (UTSA)[3].

Basic descriptive statistics for the students attending these schools are provided in Table 1 for both the full sample of enrollees and the analysis sample for students "near" the GPA cutoff at the end of their first semester of college—we follow the literature and use a bandwidth of 0.6 GPA units. The schools are shown to have very different student populations based on baseline characteristics. Whereas the average student at UT-Austin is ranked in the top 13th percentile in her graduating high school class, the average student attending UTSA is ranked in the top 35th percentile. For three of the schools the minority population makes up 10-20% of the student body, but for UTSA the figure is 50%. The average student at UT-Austin scored over 100 points higher on his SAT test than the average student at Texas Tech and nearly 200 points higher than the average student at UT-SA. Many of these differences across schools are also found in the analysis samples, where we focus on students who are "near" the GPA cutoff after their first semester (i.e. within 0.6 GPA units).

Descriptive statistics of student outcomes are provided in Table 2 for both the full sample of enrollees and analysis sample. We again see large differences across schools in student performance. Only 15% of students at TAMU were on academic probation while nearly 40% of students at UT-SA were on academic probation after the first semester. Persistence in school after the first year is approximately 90% at UT-Austin and TAMU but 80% at Texas Tech and 59% at UT-SA, but it is important to note that students who transfer schools are also counted as a non-persisting student in this measure.

Academic Probation Policies

[3] Unfortunately, the sample sizes from Rice University and Southern Methodist University were too small to include in this paper.

Several features of the academic probation policies are quite similar across universities. For our sample, each school uses a GPA threshold of 2.0 for the first semester enrolled. At all of the schools, students are notified of their academic status before the start of their second semester and the standards they need to meet to change their status. Though they all have “sharp” cutoffs, the details of the schools’ policies vary widely. First, each of the schools has a very different policy regarding academic dismissal or suspension, the more severe punishment often following probation. Texas A&M and UT Austin have floating GPA cutoffs for dismissal that vary with credits earned. UT San Antonio places students on academic dismissal if they fail to reach the cutoff while they are on probation. Texas Tech “continues” students on probation if their semester GPA, but not their cumulative GPA, stays below 2.0, and dismisses students if both averages are below 2.0. Most of the schools set limits on the number of courses students may elect while on academic probation. UT Austin is the only school in our dataset that sets a minimum course load for students on probation, at 12 semester hours. Texas Tech and UT San Antonio cap semester course loads for students on probation at 16 and 13 semester hours, respectively.

In order to help students lift their GPA’s, several of the schools have instituted special advising programs. Texas Tech and UT San Antonio require students on probation to seek remedial advising. In addition, Texas Tech mandates that first year students on probation take a “success course” and pay an extra fee for it. Texas A&M only requires advising if the student is on financial aid. Some schools also seek to discourage students on probation from participating in extracurricular activities so that they will focus more on academics. These extra features of each academic probation programs are part of the “package” of effects that we will estimate.

Empirical Specification

In order to use an RD research design to compare students on either side of the academic probation threshold, several conditions need to be met in order for these students to be valid counterfactuals (Lee and Lemieux 2009). One condition is that students must not be able to perfectly forecast their academic performance and thus be able to attempt to manipulate their first semester GPA to push themselves over the threshold. If they are able to do this, then the RD estimator would be potentially comparing students who were just below the cutoff and did not exert this "extra effort" versus those students who did and therefore may not be good comparisons. These tests amount to plotting the densities of the "running variable" (first semester GPA, in this case) to visually and statistically examine evidence of "clumping" above the threshold (McCrary 2008).

Figure 1 follows LSO and presents the density plot for students from one of the universities in the data, TAMU, using cell sizes of 0.05 GPA units. Using each of these bins as an observation, the figure superimposes the predicted cell sizes based on using local linear regression with rectangular kernel weights and a bandwidth of 0.6, following LSO and recentering the GPA measures at the threshold (2.0):

$$count_{bin} = \beta_0 + \beta_1 GPA_{rec} + \beta_2 I(GPA_{rec} < 0) + \beta_3 GPA_{rec} * I(GPA_{rec} < 0) + \varepsilon \quad (1)$$

While the estimated discontinuity of the density is not statistically significant (see Table 3 for coefficients), the visual jump is large in magnitude (400 students). One issue with examining the density of first semester GPA is the mechanical "clumping" of students at certain values due to the GPA scale used at the universities. Simply because of the GPA scale, where grade-points are typically awarded in units of 0.5 or 0.25, we would expect a disproportionate number of students to have a GPA of exactly 2.0 even in the absence of any issues of students purposely attempting to achieve a GPA above the 2.0 academic probation cutoffs. Consistent with this, we also see a similar "clumping" of students at a GPA value of 2.5 in the figure. In order to further investigate this issue, we redraw the figure (Figure 2), where we have eliminated those students who received exactly a 2.0 GPA.[4] As can be seen in the figure, there is a noticeable change in the estimated discontinuity; in fact, as we show in Table 3, the magnitude is reduced by nearly 90% and the sign of the coefficient is reversed. We therefore consider this as evidence against any purposeful manipulation of the first semester GPA by students in order to achieve a value slightly above the cutoffs. In unreported figures, the other universities face similar issues (see Table 3 for coefficient estimates). The results are similar with different bandwidths and bin sizes (results available upon request).

[4] Barreca et al. (2010) also use this design in their application of GPA data.

As a second check on the validity of the design, researchers often examine whether the observable characteristics of the individuals are continuous through the discontinuity in the running variable (Lee and Lemiuex 2009). We examine this in Table 4 by focusing on SAT score, gender, and race/ethnicity by estimating the following specification:

$$X = \alpha(GPA_{rec}) + \delta 1(GPA_{rec} < 0) + \beta(GPA_{rec}) * 1(GPA_{rec} < 0) + \varepsilon \qquad (2)$$

where X is the student characteristic of interest (e.g. minority status), GPA is recentered at zero, and δ is the coefficient of interest. The estimates use clustered standard errors at the GPA-level (Lee and Card 2008)[5]. Results show that for each school there is no evidence that, for example, more able students manipulate their academic performance so that they are more likely to be slightly above the GPA threshold. Each background characteristic does not show a discontinuity at the academic probation threshold, indicating the validity of the RD design. We provide selected figures of these results in the Appendix in Figures 1A and 2A.

Finally, we also note that our analysis uses the "sharp" RD design, as students who receive exactly a 2.0 are not placed on academic probation but students with a GPA of 1.99 are placed on academic probation with probability one. This feature of our data is shown for the case of Texas Tech in Figure 3.

Main Results

The evidence from the last section is consistent with the validity of the RD design in this context. Further, the sharp discontinuity in academic probation status allows any associated discontinuities in student college performance to be interpreted as the causal effect of academic probation status at the end of the first semester of their freshman year. Thus, we now estimate college achievement outcomes for students who are "barely" placed on academic probation status versus those who "barely" earn a GPA above the threshold. The results are estimated using variants of the following specification:

$$Y = \alpha(GPA_{rec}) + \delta 1(GPA_{rec} < 0) + \beta(GPA_{rec}) * 1(GPA_{rec} < 0) + \varepsilon \qquad (3)$$

[5] Note that Lee and Card suggest clustering standard errors when using a discretized running variables. Although GPA may be "close" to continuous over time, since we examine a first semester GPA measure, the "clumpiness" of GPA during this time creates a non-continuous variable.

In Table 5, we examine short term effects of academic probation, including persistence into the second semester and third semester as well as second semester GPA and an indicator of whether the students improved his or her GPA in the second semester. Figures 4A-4D present the graphical evidence of the estimates. In column 1 the results show small point estimates on second semester persistence for the schools, and three have a negative sign. In the appendix, we show tables that indicate the robustness of our results to changes in bandwidth or specification (Tables 1A-4A).

In Column 2, for the 90-95% of students who return for their second semester, we examine students' (recentered) second semester GPA. For all the schools, students who are placed on academic probation earn second semester GPAs that are higher by 0.1-0.2 points[6]. For this outcome, LSO find an increase of 0.23 GPA units, which is at the high end of our range of results. In Column 3, rather than examining GPA in levels, we examine whether students improve their GPA during the second semester. We find discontinuities in improvements of between 7 an 18 percentage points across the universities, and generally, students who are placed on academic probation in the less selective universities are more likely to improve. LSO find effects of 10 percentage points for students from a single Canadian university.

We extend our analysis to third semester persistence and begin to find larger effects of dropout in Column 4. At each of the universities, students are between 4-10 percentage points less likely to remain enrolled, which is between 25-50% of the baseline rates across schools. Likewise, LSO (Table 4) show effects on dropping out at third semester following being placed on academic probation of 1.8 percentage points (40% of their baseline rate). Again, note that these effects are conditional on persisting though the second semester.

In Table 6 we examine subsequent GPA performance for those students who persist in school. Figures 5A-5C present graphical evidence behind these estimates. Overall, by the end of their second year, students who received academic probation at the end of their first semester had slightly higher GPAs of 0.03-0.1 points (only TAMU is statistically significant). The effects fade out further by the end of the third year (Column

[6] As LSO note, these estimates may be biased by the effect of academic probation on which types of students persist in the university. If low ability students attrite, the impact on GPA would be positively biased and vice-versa.

2) and are either zero or potentially negative by the 4th year for all schools. It is important to note that these effects are estimated from a selected sample of students who persist long enough to earn a GPA in the second-fourth years of college. If we assume that students who have not persisted would have had lower GPAs than those who remain, then these estimates would be too large, which suggests the effect of academic probation on later GPA is likely small and potentially negative. As the sample sizes show, there is also substantial attrition (including transfers) from these colleges over the four years examined in Table 6. It is also important to note that "control students" may also be placed on academic probation over this time period, so that the long term effects become more difficult to conclusively estimate.

In Table 7 we follow LSO and examine graduation rates. Note that the sample sizes are reduced because of right censoring due to the data windows we have available[7]. Like LSO, we find mainly small and often negative effects on graduation in 4, 5, and 6 years, which is some suggestion that students who were close to being placed on academic probation after their first semester but were slightly above the cutoff seem to struggle during their college careers in a similar way as those on academic probation (and many of the students likely will be placed on academic probation in subsequent semester).

Heterogeneity of Effects

One key finding highlighted in LSO is the substantial heterogeneity in the effects of academic probation status, however they are only able to examine this issue at a single university in Canada and are confined by examining differences by gender, language of origin, and a rough measure of high school performance. LSO proposed a simple conceptual framework that fit their data reasonably well—basically, "low ability" students will gain information from being placed on academic probation that they use to update their beliefs about whether continuing in college is a good investment. We extend their analysis by examining additional sources of heterogeneity in student characteristics as well as by examining four universities of varying selectivity. For example, LSO find

[7] For example, for students who matriculate in 2000, we cannot measure six-year graduate rates if the data stop in 2004.

larger effects for low ability students and females when examining second semester GPA. In Table 8 we reexamine these effects using our data. Our results suggest less clear patterns across the multiple universities. For example, for UT-Austin, the effects on low ability students are negative but the opposite is true at TAMU; Texas Tech and UT-SA show similar results for high and low ability students. Similarly, our gender results show large positive effects for males at UTSA and TAMU but similar effects at UT-Austin and Texas Tech. We also do not find clear patterns between race/ethnicity categories. For graduation rates, LSO find larger impacts on high ability students and males. We do not find any consistent results across groups. Indeed, we are able to extend the LSO analysis by separating students by income level of high school, SAT score, whether they enroll at the university with a social network (measured as students from their graduating high school)[8]. While we find suggestive evidence of heterogeneity in these extensions (though few differences are statistically different), none of the effects are consistent across schools (results are available upon request). We interpret this evidence as too varied to fit the simple stylized framework outlined in LSO and suggest the need for further investigation using richer (potentially experimental) research designs in order to pull apart the effect of the various elements of colleges' academic probation policies.

Conclusions

While nearly all colleges and universities in the United States have policies that create academic probation status based on GPA performance, almost nothing is known about the use of this designation and the programs that accompany it on college success. We are aware of only a single paper in the economics literature to examine these issues, which uses data from a single Canadian university. Thus it is unclear how general the findings are along measures of university quality or different institutional settings across countries. This paper uses a regression discontinuity approach to estimate the effects of academic probation programs at four universities of varying selectivity in Texas. Results suggest that academic probation status following the first semester of college may serve as a short term "wake up call" to some students in that second semester performance is improved. However, our findings also suggest that this short term boost in performance

[8] See Fletcher and Tienda (2009) for further details of this measure

fades out over time. Specifically, we find that students who receive academic probation after their first semester have the same graduation and persistence rates as students who perform poorly but do not receive probation. We also find important differential responses to academic probation based on pre-determined student characteristics as well as high school of origin, however none of the heterogeneous effects are consistent across universities. This result contrasts with earlier research on this topic by limiting the generalizability of specific types of heterogeneity of responses to these policies. Overall, we also do not find strong evidence that academic probation programs at colleges in the US affect medium and long term outcomes across a range of selectivity of colleges, but a partial explanation of this finding is that "control students" may become treated after the first semester, which would reduce the estimated effects. We also note that future research should further test these findings with data from schools outside of Texas and with larger sets of schools. In this way, future work may be able to unpack the particular elements of school academic probation policies that lead to these outcomes and may also be able to explain the heterogeneity of effects based on student characteristics.

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Table 1
Descriptive Statistics: Student Characteristics of Enrollees to Four Texas Universities 1990-2002

University Full Sample of Enrollees Variable	UT Austin N	 Mean	 SD	TAMU N	 Mean	 SD	Texas Tech N	 Mean	 SD	UT-SA N	 Mean	 SD
High School Rank Percentile	74550	12.84	11.88	62401	14.04	11.99	30805	25.82	18.39	24040	33.13	21.68
Hours Earned in First Semester	81200	17.21	8.11	67311	12.02	2.71	33867	14.53	4.87	27032	10.12	4.34
Male	81200	0.50	0.50	67311	0.49	0.50	34876	0.49	0.50	27028	0.47	0.50
Lower Income	81200	0.52	0.50	67311	0.47	0.50	34899	0.51	0.50	27032	0.59	0.49
Black or Hispanic	81200	0.18	0.38	67311	0.13	0.34	34899	0.12	0.32	27032	0.47	0.50
SAT or Converted ACT	81188	1213.40	141.94	67194	1164.03	137.49	24748	1101.27	133.04	19926	997.02	134.66
Feeder School	81200	0.23	0.42	67311	0.17	0.37	30791	0.12	0.32	25712	0.08	0.26
Classmates from Same High School	81200	94.22	114.17	67277	60.12	70.14	34899	43.51	79.06	25712	59.30	69.34
Within Bandwidth (Analysis Sample)	**UT Austin**	**21%**		**TAMU**	**32%**		**Texas Tech**	**22%**		**UT-SA**	**32%**	
Variable	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
High School Rank Percentile	15461	17.26	13.18	19704	17.34	12.57	6682	33.18	18.08	7618	34.27	21.14
Hours Earned in First Semester	16715	13.64	2.91	21162	11.53	2.45	7681	13.17	3.80	8421	11.30	2.45
Male	16715	0.54	0.50	21162	0.51	0.50	7733	0.56	0.50	8421	0.48	0.50
Lower Income	16715	0.59	0.49	21162	0.49	0.50	7737	0.53	0.50	8421	0.60	0.49
Black or Hispanic	16715	0.23	0.42	21162	0.17	0.38	7737	0.15	0.36	8421	0.50	0.50
SAT or Converted ACT	16713	1156.55	128.28	21131	1120.18	123.82	5138	1057.82	117.14	6111	975.91	124.95
Feeder School	16715	0.18	0.39	21162	0.14	0.35	6682	0.12	0.32	7982	0.07	0.25
Classmates from Same High School	16715	75.25	98.11	21153	54.46	65.47	7737	40.55	77.05	7982	57.59	68.29

Notes: Low income is a high school based measure indicating a high proportion of classmates on free/reduced lunch. Feeder school is a high school based measure indicating whether there is a history of sending a large number of students to the university in question. “Classmates from same high school” is a count of individuals from the same high school graduating class who attend college together.

Table 2
Descriptive Statistics: Student Academic Outcomes of Enrollees to Four Texas Universities 1990-2002

University	UT Austin			TAMU			Texas Tech			UT-SA		
Full Sample of Enrollees												
Variable	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD
On Probation After First Semester	81200	0.12	0.33	67311	0.15	0.36	34899	0.12	0.32	27032	0.39	0.49
Ever on Probation	94951	0.28	0.45	67311	0.23	0.42	34899	0.19	0.39	27032	0.57	0.50
First Semester Distance to Cutoff	81200	1.14	0.60	67311	0.92	0.58	34899	1.07	0.58	27032	0.91	0.61
Second Sem. Distance to Cutoff	78080	1.11	0.59	64534	0.95	0.58	31903	1.04	0.58	23143	0.92	0.62
4th Semester Distance to Cutoff	67662	1.10	0.58	59369	1.03	0.57	24181	1.08	0.59	12829	0.90	0.61
6th Semester Distance to Cutoff	59000	1.18	0.59	56513	1.11	0.58	20172	1.15	0.61	8633	0.96	0.63
8th Semester Distance to Cutoff	49961	1.23	0.59	53813	1.19	0.60	17200	1.21	0.62	6565	1.01	0.62
Persisted for Second Semester	81200	0.96	0.19	67311	0.96	0.20	34899	0.91	0.28	27032	0.86	0.35
Persisted for Third Semester	81194	0.88	0.33	67311	0.88	0.33	34820	0.80	0.40	22742	0.59	0.49
Improved GPA in Second Semester	78080	0.41	0.49	64534	0.48	0.50	31903	0.41	0.49	23143	0.38	0.49
4 Year Graduation Rate	62626	0.47	0.50	67295	0.33	0.47	23256	0.25	0.44	17192	0.05	0.21
5 Year Graduation Rate	56150	0.66	0.48	60611	0.69	0.46	19845	0.51	0.50	15080	0.14	0.35
6 Year Graduation Rate	49820	0.70	0.46	54204	0.76	0.43	17133	0.56	0.50	13117	0.20	0.40
	UT Austin			TAMU			Texas Tech			UT-SA		
Within Bandwidth (Analysis Sample)		21%			31%			22%			31%	
Variable	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD
On Probation After First Semester	16715	0.31	0.46	21162	0.29	0.46	7737	0.27	0.44	8421	0.43	0.49
Ever on Probation	16715	0.50	0.50	21162	0.44	0.50	7737	0.45	0.50	8421	0.69	0.46
First Semester Distance to Cutoff	16715	0.35	0.15	21162	0.33	0.16	7737	0.34	0.15	8421	0.35	0.14
Second Sem. Distance to Cutoff	15849	0.72	0.48	20261	0.62	0.43	6919	0.66	0.46	7696	0.71	0.55
4th Semester Distance to Cutoff	13331	0.79	0.52	17965	0.76	0.49	4756	0.77	0.51	4524	0.78	0.57
6th Semester Distance to Cutoff	11181	0.88	0.55	16692	0.85	0.53	3827	0.86	0.56	2941	0.83	0.60
8th Semester Distance to Cutoff	9567	0.97	0.58	15826	0.97	0.57	3260	0.94	0.59	2245	0.90	0.60
Persisted for Second Semester	16715	0.95	0.22	21162	0.96	0.20	7737	0.89	0.31	8421	0.91	0.28
Persisted for Third Semester	16715	0.82	0.39	21162	0.84	0.37	7731	0.73	0.45	7169	0.66	0.47
Improved GPA in Second Semester	15849	0.62	0.48	20261	0.63	0.48	6919	0.59	0.49	7696	0.43	0.50
4 Year Graduation Rate	13919	0.31	0.46	21156	0.22	0.41	5446	0.14	0.35	5527	0.03	0.18
5 Year Graduation Rate	12853	0.49	0.50	19412	0.58	0.49	4697	0.38	0.48	4911	0.13	0.34
6 Year Graduation Rate	11644	0.54	0.50	17679	0.67	0.47	4177	0.45	0.50	4284	0.19	0.40

Table 3
Density Tests for Discontinuity in Number of Individuals for First-Semester GPA

	UT	UT	TAMU	TAMU	Tech	Tech	UT-SA	UT-SA
Bin Size	.05	.05	.05	.05	.05	.05	.05	.05
Bandwidth	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Sample	Full	no 2.0's	Full	no 2.0's	Full	no 2.0's	Full	no 2.0's
Discontinuity Indicator	-518.794	199.559	-419.151	49.650	-155.5	29.91	-329.337	256.464
	(585.317)	(311.744)	(469.264)	(350.796)	(192.7)	(139.4)	(540.747)	(281.178)
Indicator*Bin	-726.853	-2,486.084**	467.902	-680.182	-156.1	-610.2	437.539	-997.077
	(1,667.718)	(1,116.070)	(1,398.056)	(1,213.238)	(607.3)	(545.1)	(1,468.072)	(936.036)
Bin Midpoint	702.937	2,462.168**	489.371	1,637.455	371.7	825.8	-382.448	1,052.168
	(1,558.030)	(944.344)	(1,354.365)	(1,162.122)	(577.7)	(511.6)	(1,306.448)	(654.012)
Constant	942.119*	223.766	1,295.356***	826.555**	432.5**	247.1*	673.151	87.350
	(540.520)	(216.217)	(446.892)	(319.943)	(179.7)	(120.5)	(483.386)	(142.535)
Observations	24	23	23	22	22	21	23	22
R-squared	0.321	0.458	0.519	0.612	0.477	0.579	0.067	0.125

Notes: Sample includes full analysis sample ("Full") or the full analysis sample expect those who earned exactly a 2.0 GPA ("no 2.0s")

Table 4
Examination of Continuity of Covariates Through the Academic Probation GPA Discontinuity

	UT	UT	UT	TAMU	TAMU	TAMU	Tech	Tech	Tech	UT-SA	UT-SA	UT-SA
Bandwidth	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Covariate	Female	SAT Score	Minority	Female	SAT Score	Minority	Female	SAT Score	Minority	Female	SAT Score	Minority
Discontinuity Indicator	0.053	13.618	-0.021	-0.005	0.141	-0.009	-0.018	5.868	-0.022	0.007	18.303	-0.053
	(0.049)	(21.289)	(0.026)	(0.037)	(8.088)	(0.013)	(0.027)	(9.529)	(0.024)	(0.046)	(18.664)	(0.042)
Recentered GPA	-0.088	7.346	-0.092	-0.045	32.130**	-0.084***	-0.097***	17.671	-0.023	-0.002	48.191	-0.133
	(0.093)	(41.590)	(0.057)	(0.065)	(15.367)	(0.017)	(0.036)	(12.822)	(0.026)	(0.057)	(33.424)	(0.089)
Interaction	0.130	56.864	-0.010	-0.045	-5.402	-0.010	0.070	-21.544	-0.045	-0.052	15.939	0.026
	(0.121)	(62.600)	(0.071)	(0.085)	(23.270)	(0.035)	(0.050)	(19.574)	(0.052)	(0.116)	(42.998)	(0.111)
Constant	0.548***	1,156.600***	0.248***	0.519***	1,114.422***	0.185***	0.598***	1,050.638***	0.155***	0.472***	966.828***	0.578***
	(0.037)	(15.091)	(0.018)	(0.028)	(5.352)	(0.007)	(0.020)	(6.406)	(0.013)	(0.022)	(14.409)	(0.032)
Observations	16713	16713	16713	21131	21131	21131	7690	7690	7690	6111	6111	6111

Notes: Discontinuity Indicator =1 if GPA below threshold for academic probation status (2.0), Interaction is between indicator and recentered GPA. Standard errors clustered at level of GPA in bins of 0.05 points. Bandwidth=0.6. Covariate row indicates the "outcome" of interest.

Table 5

Effects of First Semester Academic Probation Status through the Third Semester of College: RD Evidence

UT Austin	Second Semester Persistence	Recentered. 2nd Semester GPA	Second Semester Improvement	Third Semester Persistence
1st Semester GPA < Cutoff	0.007	0.136***	0.085***	-0.038*
	(0.011)	(0.052)	(0.021)	(0.022)
Constant	0.933***	0.220***	0.657***	0.835***
	(0.006)	(0.037)	(0.014)	(0.011)
Observations	16715	15849	15849	16715
TAMU	**Second Semester Persistence**	**Rec. Second Semester GPA**	**Second Semester Improvement**	**Third Semester Persistence**
1st Semester GPA < Cutoff	-0.002	0.108**	0.073**	-0.056***
	(0.008)	(0.045)	(0.028)	(0.018)
Constant	0.962***	0.241***	0.667***	0.873***
	(0.004)	(0.030)	(0.021)	(0.010)
Observations	21162	20261	20261	21162
Texas Tech	**Second Semester Persistence**	**Rec. 2nd Semester GPA**	**Second Semester Improvement**	**Third Semester Persistence**
1st Semester GPA < Cutoff	-0.033	0.230***	0.185***	-0.100***
	(0.022)	(0.051)	(0.028)	(0.032)
Constant	0.908***	0.139***	0.606***	0.730***
	(0.013)	(0.034)	(0.019)	(0.021)
Observations	7737	6919	6919	7731
UTSA	**Second Semester Persistence**	**Rec. 2nd Semester GPA**	**Second Semester Improvement**	**Third Semester Persistence**
1st Semester GPA < Cutoff	-0.015	0.149**	0.101**	-0.060*
	(0.017)	(0.068)	(0.039)	(0.034)
Constant	0.938***	-0.231***	0.424***	0.721***
	(0.012)	(0.062)	(0.035)	(0.022)
Observations	8421	7696	7696	7169

Notes: standard errors clustered at level of GPA in bins of 0.05 points. Bandwidth=0.6. Running variable controlled.

Table 6

Effects of First Semester Academic Probation Status through the Eighth Semester of College: RD Evidence

UT Austin	Rec. 4th Sem. GPA	Rec. 6th Sem. GPA	Rec. 8th Sem. GPA
1st Semester GPA < Cutoff	0.036	-0.025	0.013
	(0.035)	(0.038)	(0.048)
Constant	0.351***	0.565***	0.654***
	(0.026)	(0.025)	(0.026)
Observations	13331	11181	9567
TAMU	Rec. 4th Sem. GPA	Rec. 6th Sem. GPA	Rec. 8th Sem. GPA
1st Semester GPA < Cutoff	0.056**	0.050*	0.015
	(0.025)	(0.030)	(0.033)
Constant	0.509***	0.617***	0.770***
	(0.019)	(0.021)	(0.023)
Observations	17965	16692	15826
Texas Tech	Rec. 4th Sem. GPA	Rec. 6th Sem. GPA	Rec. 8th Sem. GPA
1st Semester GPA < Cutoff	0.032	0.010	-0.054
	(0.056)	(0.057)	(0.060)
Constant	0.488***	0.633***	0.736***
	(0.029)	(0.033)	(0.028)
Observations	4756	3827	3260
UTSA	Rec. 4th Sem. GPA	Rec. 6th Sem. GPA	Rec. 8th Sem. GPA
1st Semester GPA < Cutoff	0.115	0.032	-0.142
	(0.075)	(0.090)	(0.117)
Constant	-0.129**	0.166***	0.337***
	(0.051)	(0.056)	(0.064)
Observations	4524	2941	2245

Notes: standard errors clustered at level of GPA in bins of 0.05 points. Bandwidth=0.6. Running variable controlled.

Table 7
Effects of First Semester Academic Probation Status on Graduation Rates: RD Evidence

UT Austin	4 Year Graduation Rate	5 Year Graduation Rate	6 Year Graduation Rate
1st Semester GPA < Cutoff	0.002	0.002	0.025
	(0.018)	(0.022)	(0.021)
Constant	0.262***	0.439***	0.492***
	(0.014)	(0.016)	(0.015)
Observations	13919	12853	11644
TAMU	**4 Year Graduation Rate**	**5 Year Graduation Rate**	**6 Year Graduation Rate**
1st Semester GPA < Cutoff	0.003	-0.023	-0.036
	(0.025)	(0.032)	(0.027)
Constant	0.184***	0.555***	0.662***
	(0.022)	(0.024)	(0.018)
Observations	21156	19412	17679
Texas Tech	**4 Year Graduation Rate**	**5 Year Graduation Rate**	**6 Year Graduation Rate**
1st Semester GPA < Cutoff	-0.018	-0.003	0.034
	(0.024)	(0.041)	(0.047)
Constant	0.118***	0.336***	0.391***
	(0.016)	(0.027)	(0.033)
Observations	5446	4697	4177
UTSA	**4 Year Graduation Rate**	**5 Year Graduation Rate**	**6 Year Graduation Rate**
1st Semester GPA < Cutoff	-0.002	-0.020	-0.022
	(0.014)	(0.026)	(0.032)
Constant	0.027***	0.133***	0.198***
	(0.010)	(0.023)	(0.026)
Observations	5527	4911	4284

Notes: standard errors clustered at level of GPA in bins of 0.05 points. Bandwidth=0.6.
The sample sizes are reduced for later outcomes due to few years of available data. Running variable controlled.

Table 8

Heterogeneity of Effects of First Semester Academic Probation Status: Second Semester GPA

UT Austin							
Stratum	All	Upper Half of HS Class	Lower Half of HS Class	Female	Male	Non-Minority	Minority
First Sem. GPA Below Cutoff	0.136***	0.121**	-0.170	0.157**	0.140**	0.115**	0.196**
	(0.052)	(0.054)	(0.214)	(0.067)	(0.056)	(0.055)	(0.079)
Observations	15849	14308	353	7302	8547	12235	3603
p: effects equal			0.163		0.805		0.278
TAMU							
Stratum	All	Upper Half of HS Class	Lower Half of HS Class	Female	Male	Non-Minority	Minority
First Sem. GPA Below Cutoff	0.108**	0.116**	0.084	0.082	0.133***	0.116**	0.076
	(0.045)	(0.045)	(0.191)	(0.059)	(0.045)	(0.045)	(0.061)
Observations	20261	18508	367	9874	10387	16826	3433
p: effects equal			0.870		0.382		0.415
Texas Tech							
Stratum	All	Upper Half of HS Class	Lower Half of HS Class	Female	Male	Non-Minority	Minority
First Sem. GPA Below Cutoff	0.230***	0.235***	0.161	0.249***	0.223***	0.210***	0.327***
	(0.051)	(0.053)	(0.129)	(0.085)	(0.058)	(0.056)	(0.120)
Observations	6919	5013	968	3054	3863	5896	1022
p: effects equal			0.596				0.396
UTSA							
Stratum	All	Upper Half of HS Class	Lower Half of HS Class	Female	Male	Non-Minority	Minority
First Sem. GPA Below Cutoff	0.149**	0.142**	0.285**	0.081	0.227**	0.154*	0.139*
	(0.068)	(0.062)	(0.138)	(0.069)	(0.087)	(0.083)	(0.082)
Observations	7696	5439	1517	3979	3717	3854	3842
p: effects equal			0.273		0.043		0.877

Notes: standard errors clustered at level of GPA in bins of 0.05 points. Bandwidth=0.6

Figures

Figure 1
TAMU Density of Students Around the GPA Cutoff

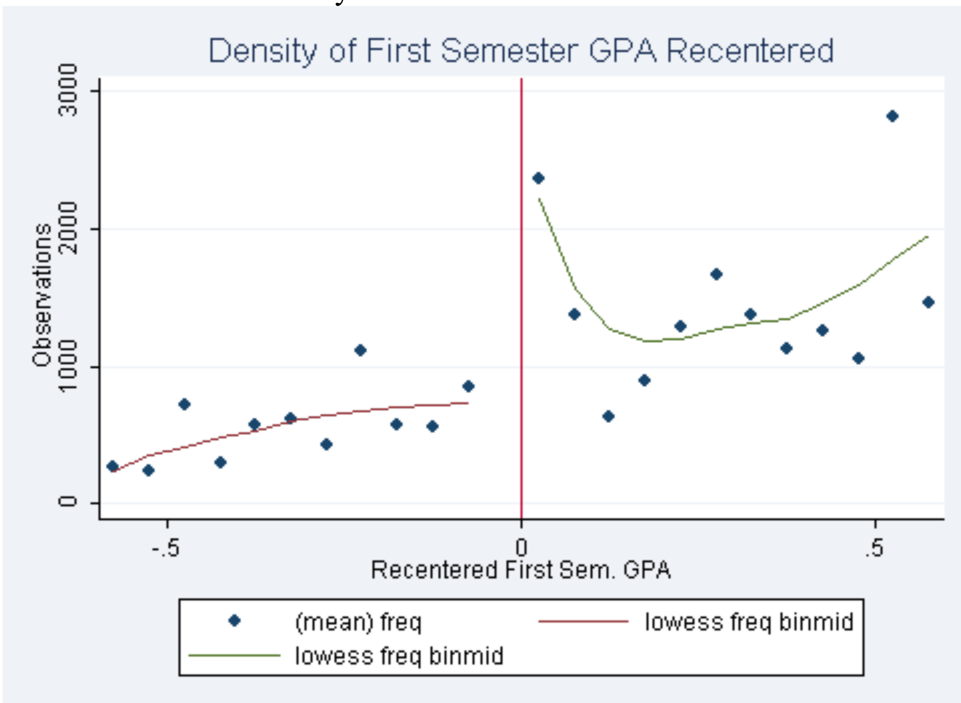


Figure 2
TAMU Density of Students Around the GPA Cutoff
Remove GPAs of Exactly 2.0

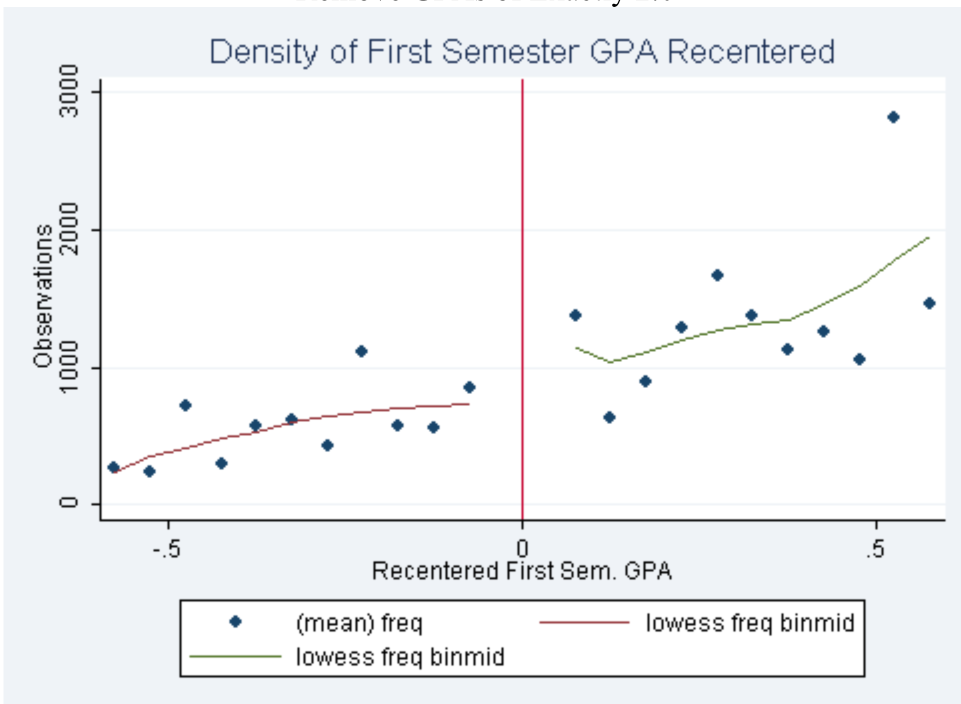


Figure 3
Evidence of the "Sharp" RD Design
Likelihood of Academic Probation Status vs. Recentered First Semester GPA
Texas Tech Students

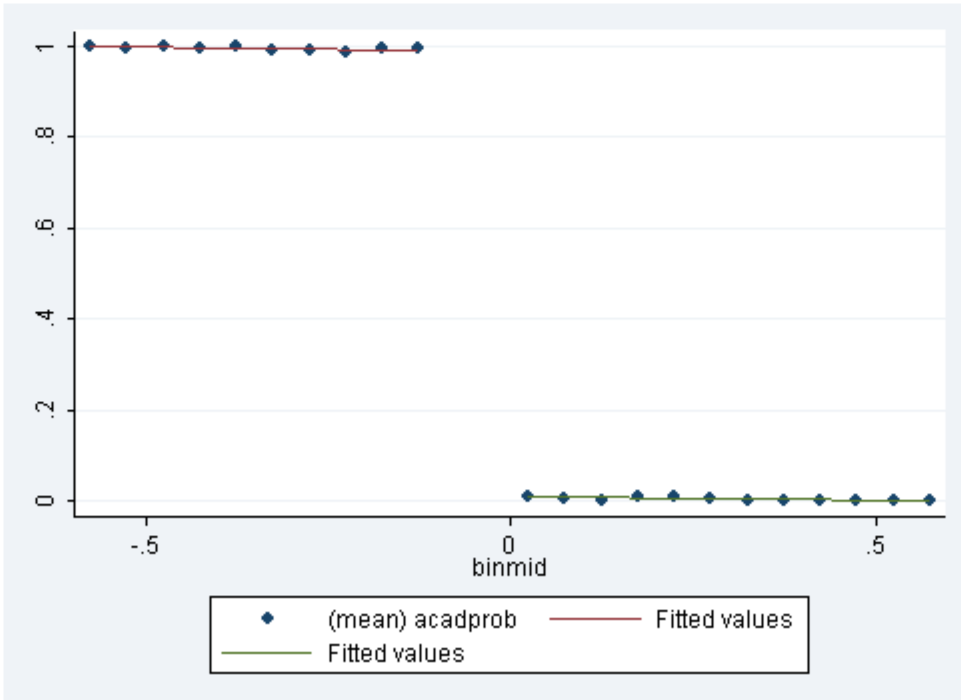
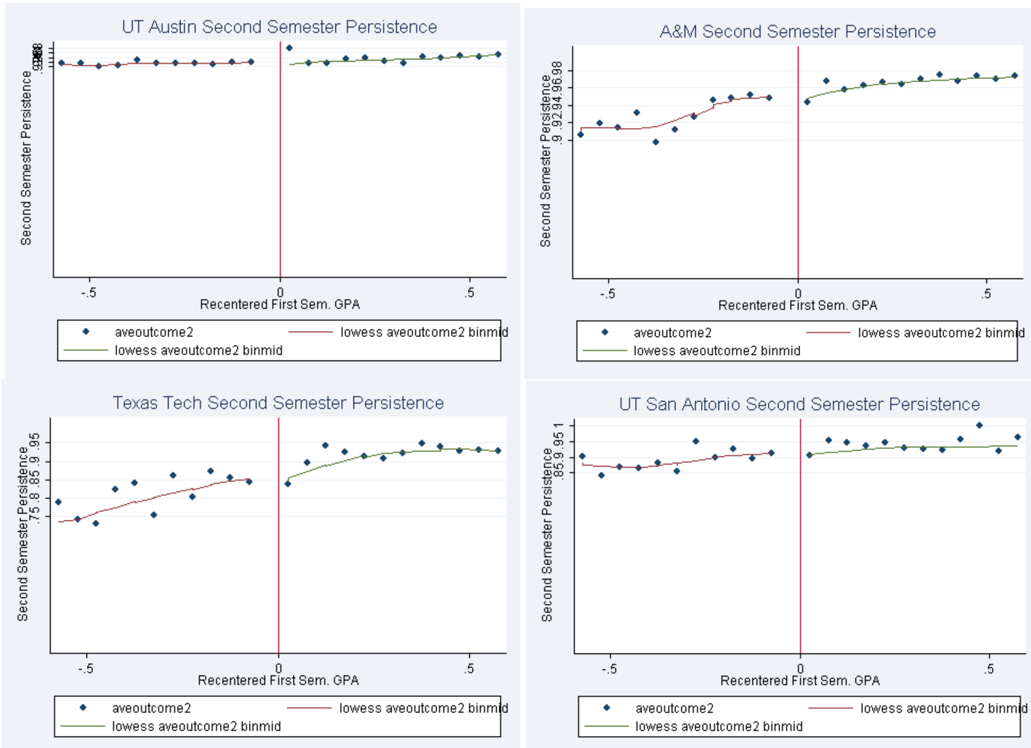


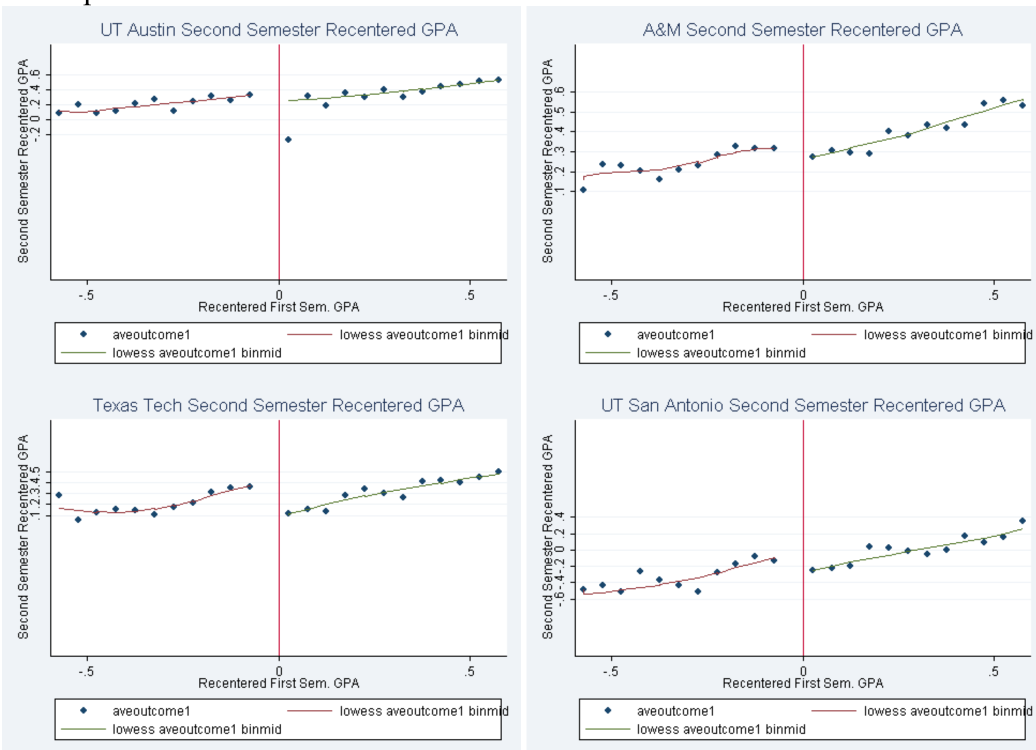
Figure 4A
Graphical Evidence of the Effects of Academic Probation on Second Semester Persistence



Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

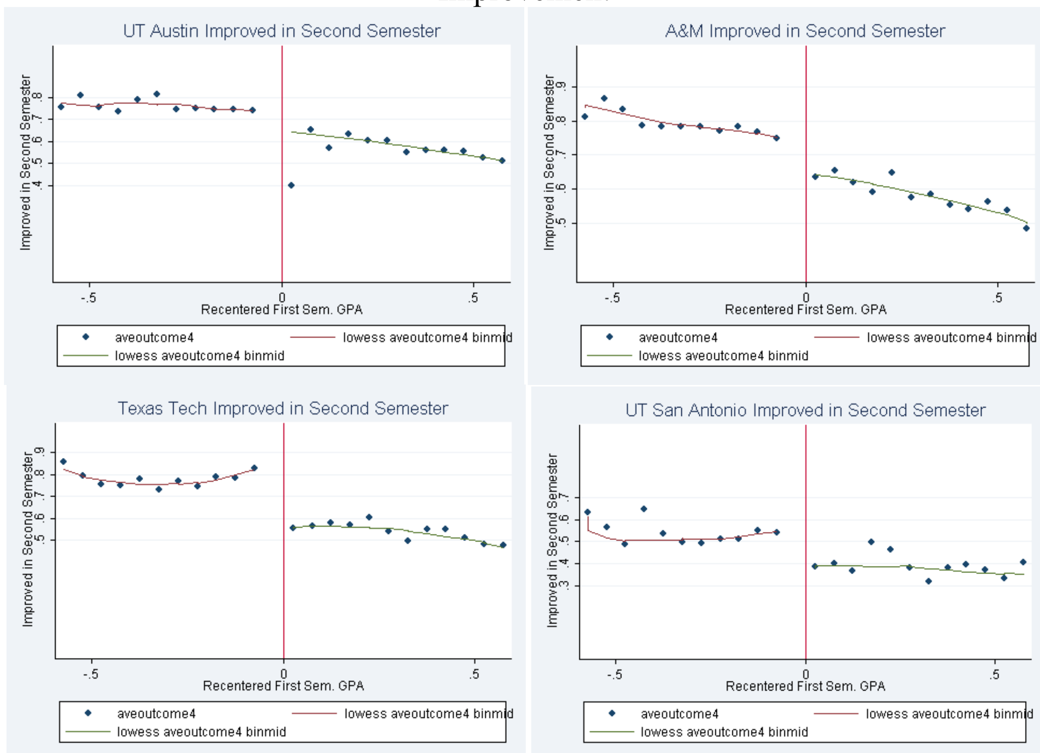
Figure 4B

Graphical Evidence of the Effects of Academic Probation on Second Semester GPA



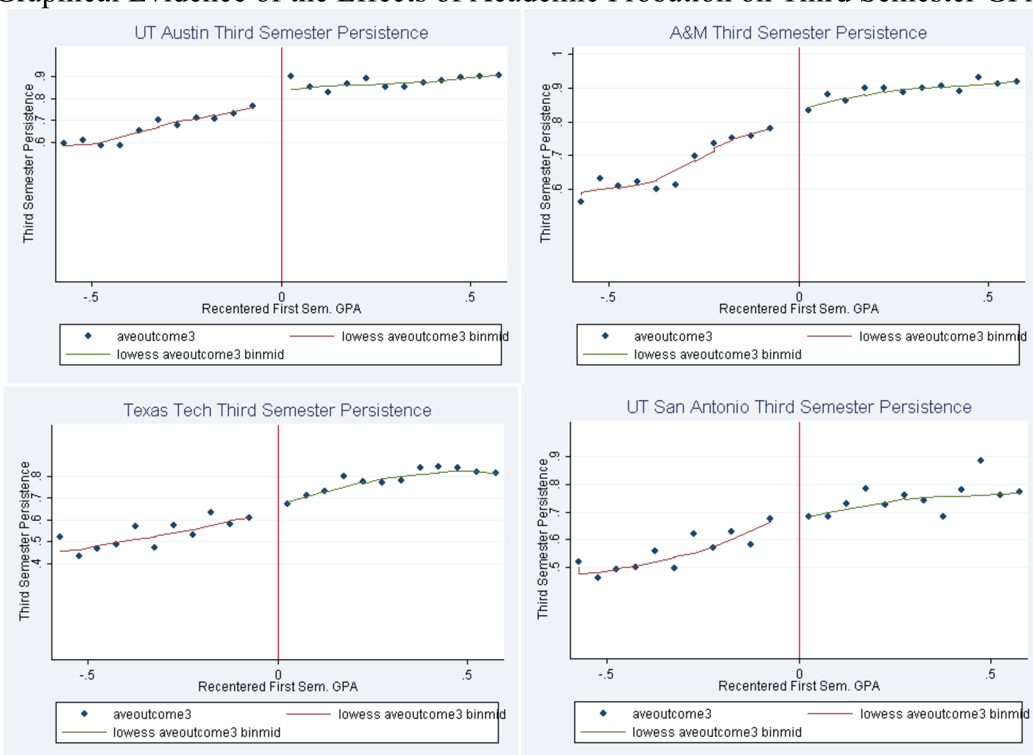
Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

Figure 4C
Graphical Evidence of the Effects of Academic Probation on Second Semester GPA Improvement



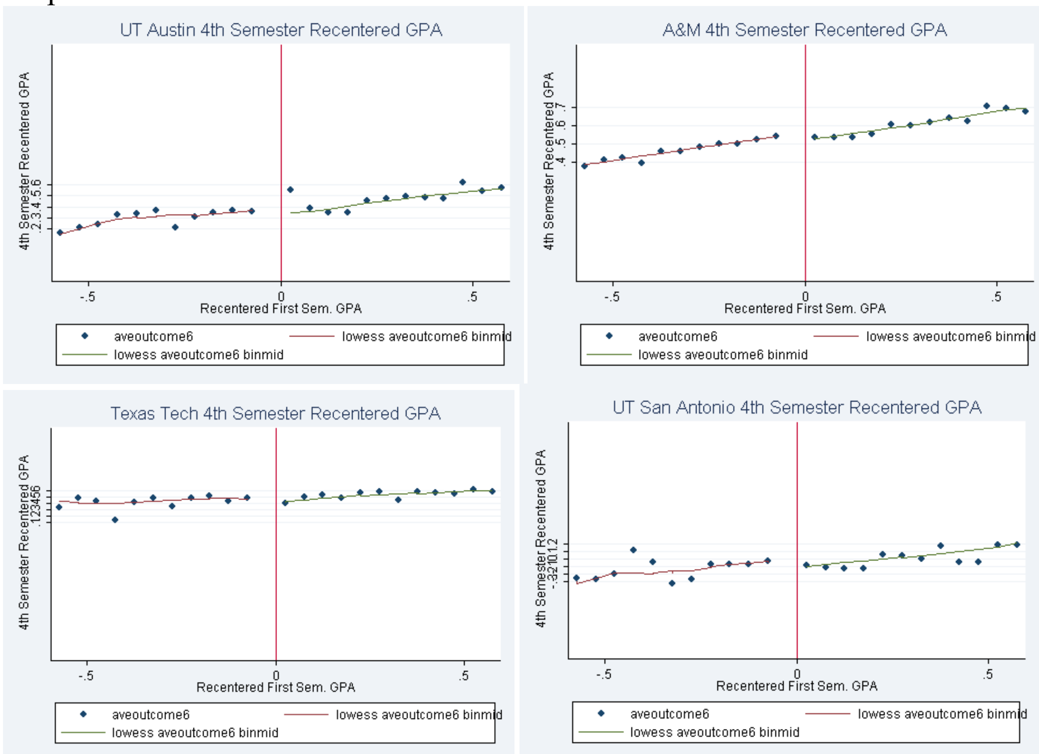
Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

Figure 4D
Graphical Evidence of the Effects of Academic Probation on Third Semester GPA



Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

Figure 5A
Graphical Evidence of the Effects of Academic Probation on 4th Semester GPA



Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

Figure 5B
Graphical Evidence of the Effects of Academic Probation on 6th Semester GPA

Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

Figure 5C

Graphical Evidence of the Effects of Academic Probation on 8th Semester GPA

Notes: Bin Size=0.05 GPA Points, Bandwidth=0.6. Lowess Smoother estimated on each side of the discontinuity

Appendix Figures

Figure 1A
No Estimated Discontinuity for Observable Characteristics
Minority Status at TAMU

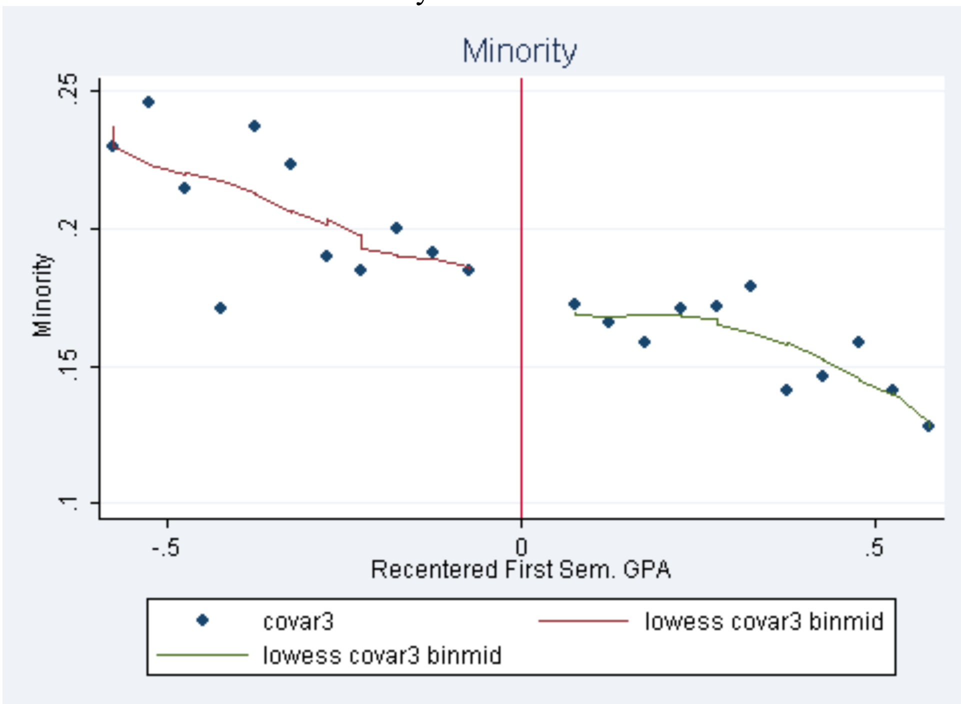
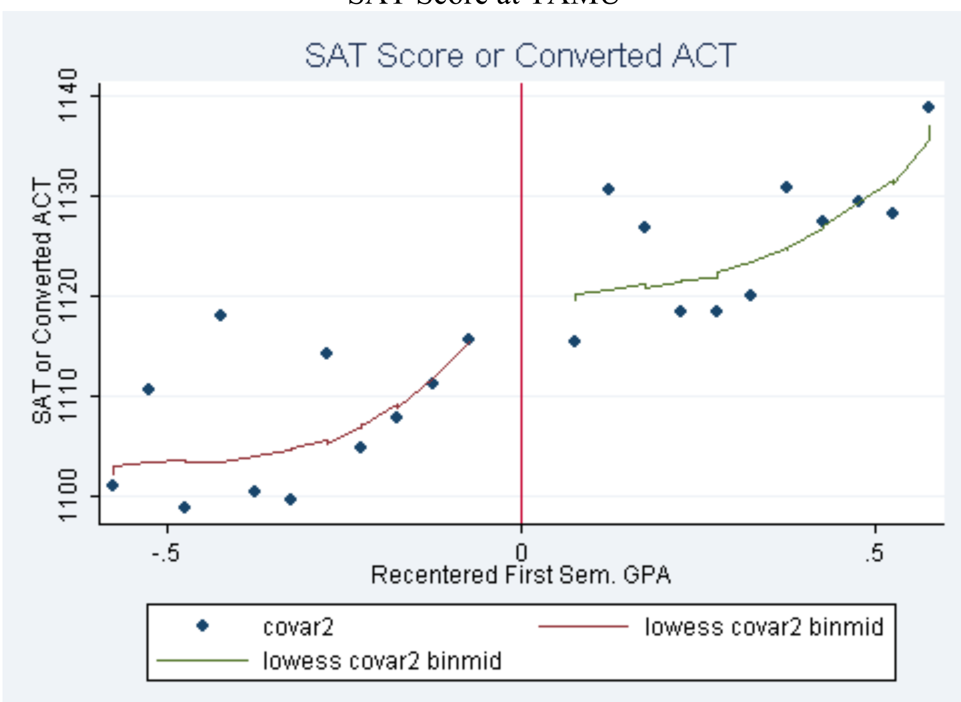


Figure 2A
No Estimated Discontinuity for Observable Characteristics
SAT Score at TAMU



Appendix Tables

Table 1A

Robustness of Findings for TAMU: Changes to Bandwidth and Specification

Specification	**Baseline (From tables)**	**Baseline (w/ controls)**	**Linear**	**Linear**	**Linear**	**Linear**	**Polynomial**
Bandwidth	**0.6**	**0.6**	**0.4**	**0.5**	**0.7**	**0.8**	**0.6**
Second Sem Persistence	-0.002	-0.002	0.011	0.004	0.005	0.012	0.003
	(0.008)	(0.008)	(0.011)	(0.010)	(0.008)	(0.008)	(0.014)
Observations	21162	19699	21163	15894	24651	29442	21162
2nd Semester GPA	0.108**	0.116***	0.123**	0.114**	0.130***	0.156***	0.105
	(0.045)	(0.040)	(0.056)	(0.052)	(0.040)	(0.038)	(0.073)
Observations	20261	18870	24716	29979	45925	54431	20261
Second Sem Improvement	0.073**	0.073***	0.075**	0.079**	0.085***	0.099***	0.076*
	(0.028)	(0.024)	(0.033)	(0.030)	(0.025)	(0.022)	(0.044)
Observations	20261	18870	12485	15205	23573	28170	20261
Third Sem Persistence	-0.056***	-0.054***	-0.027	-0.039*	-0.053***	-0.049***	-0.032
	(0.018)	(0.019)	(0.023)	(0.022)	(0.017)	(0.015)	(0.031)
Observations	21162	19699	13069	15894	24651	29442	21162
Rec. 4th Sem. GPA	0.056**	0.053**	0.059*	0.066**	0.056**	0.071***	0.063
	(0.025)	(0.022)	(0.034)	(0.032)	(0.026)	(0.025)	(0.052)
Observations	17965	16735	10938	13411	20925	25105	17965
Rec. 6th Sem. GPA	0.050*	0.040	0.064*	0.051	0.032	0.038	0.067
	(0.030)	(0.025)	(0.035)	(0.035)	(0.030)	(0.028)	(0.048)
Observations	16692	15561	10082	12384	19469	23452	16692
Rec. 8th Sem. GPA	0.015	0.021	-0.004	0.007	0.011	0.020	-0.021
	(0.033)	(0.026)	(0.037)	(0.037)	(0.033)	(0.032)	(0.050)
Observations	15826	14774	9525	11712	18496	22343	15826
4 Year Graduation Rate	0.003	-0.001	-0.012	0.002	-0.005	-0.002	-0.032
	(0.025)	(0.020)	(0.031)	(0.032)	(0.024)	(0.021)	(0.042)
Observations	21156	19693	13066	15891	24644	29435	21156
5 Year Graduation Rate	-0.023	-0.027	-0.021	-0.011	-0.019	-0.017	-0.020
	(0.032)	(0.029)	(0.039)	(0.037)	(0.030)	(0.027)	(0.056)
Observations	19412	18051	12094	14667	22571	26858	19412
6 Year Graduation Rate	-0.036	-0.039	-0.042	-0.030	-0.034	-0.028	-0.050

	(0.027)	(0.027)	(0.033)	(0.032)	(0.025)	(0.022)	(0.047)
Observations	17679	16418	11089	13405	20506	24311	17679

Notes: Control variables include gender, race, and SAT score, high school rank, and year dummies

Table 2A
Robustness of Findings for UT-Austin: Changes to Bandwidth and Specification

Specification	**Baseline (From tables)**	**Baseline (w/ controls)**	**Linear**	**Linear**	**Linear**	**Linear**	**Polynomial**
Bandwidth	**0.6**	**0.6**	**0.4**	**0.5**	**0.7**	**0.8**	**0.6**
Second Sem Persistence	0.007	0.007	-0.010	-0.002	0.010	0.012	-0.009
	(0.011)	(0.012)	(0.017)	(0.014)	(0.009)	(0.009)	(0.025)
Observations	16715	15461	9596	11602	19421	24569	16715
2nd Semester GPA	0.136***	0.127**	0.062	0.117*	0.157***	0.165***	0.089
	(0.052)	(0.055)	(0.082)	(0.066)	(0.051)	(0.046)	(0.102)
Observations	15849	14661	9045	10960	18438	23385	15849
Second Sem Improvement	0.085***	0.078***	0.050	0.082***	0.098***	0.101***	0.049
	(0.021)	(0.023)	(0.036)	(0.028)	(0.021)	(0.019)	(0.046)
Observations	15849	14661	9045	10960	18438	23385	15849
Third Sem Persistence	-0.038*	-0.040	-0.076**	-0.052**	-0.037*	-0.039**	-0.084*
	(0.022)	(0.025)	(0.031)	(0.026)	(0.020)	(0.019)	(0.046)
Observations	16715	15461	9596	11602	19420	24568	16715
Rec. 4th Sem. GPA	0.036	0.032	0.007	0.032	0.019	0.046	0.015
	(0.035)	(0.038)	(0.052)	(0.052)	(0.034)	(0.034)	(0.072)
Observations	13331	12257	7509	9131	15467	19723	13331
Rec. 6th Sem. GPA	-0.025	-0.035	-0.033	0.016	-0.031	-0.007	-0.039
	(0.038)	(0.038)	(0.048)	(0.043)	(0.035)	(0.032)	(0.068)
Observations	11181	10254	6220	7594	12976	16685	11181
Rec. 8th Sem. GPA	0.013	0.017	0.014	0.001	-0.008	0.019	-0.067
	(0.048)	(0.052)	(0.064)	(0.056)	(0.045)	(0.040)	(0.084)
Observations	9567	8788	5268	6436	11108	14373	9567
4 Year Graduation Rate	0.002	-0.001	-0.021	-0.016	-0.019	-0.026	-0.048
	(0.018)	(0.018)	(0.027)	(0.025)	(0.020)	(0.016)	(0.038)
Observations	13919	12860	7960	9602	16102	20369	13919
5 Year Graduation Rate	0.002	-0.005	-0.051	-0.034	-0.011	-0.001	-0.101**
	(0.022)	(0.023)	(0.031)	(0.028)	(0.022)	(0.018)	(0.043)
Observations	12853	11882	7348	8878	14863	18761	12853
6 Year Graduation Rate	0.025	0.024	-0.052	-0.008	0.021	0.024	-0.093**
	(0.021)	(0.022)	(0.034)	(0.028)	(0.023)	(0.019)	(0.046)

Observations	11644	10791	6659	8041	13465	16980	11644

Notes: Control variables include gender, race, and SAT score, high school rank, and year dummies

Table 3A
Robustness of Findings for Texas Tech: Changes to Bandwidth and Specification

Specification	Baseline (From tables)	Baseline (w/ controls)	Linear	Linear	Linear	Linear	Polynomial
Bandwidth	**0.6**	**0.6**	**0.4**	**0.5**	**0.7**	**0.8**	**0.6**
Second Sem Persistence	-0.033	-0.035*	-0.037	-0.038	-0.026	-0.032*	-0.032
	(0.022)	(0.020)	(0.028)	(0.025)	(0.022)	(0.018)	(0.040)
Observations	7737	5126	4662	5685	9375	11479	7737
2nd Sem GPA	0.230***	0.177***	0.293***	0.260***	0.250***	0.227***	0.373***
	(0.051)	(0.059)	(0.068)	(0.058)	(0.044)	(0.043)	(0.090)
Observations	6919	4605	4141	5080	8385	10321	6919
Second Sem Improvement	0.185***	0.154***	0.216***	0.213***	0.190***	0.178***	0.284***
	(0.028)	(0.037)	(0.037)	(0.032)	(0.026)	(0.025)	(0.045)
Observations	6919	4605	4141	5080	8385	10321	6919
Third Semester Persistence	-0.100***	-0.127***	-0.077*	-0.072**	-0.089***	-0.113***	-0.029
	(0.032)	(0.032)	(0.041)	(0.036)	(0.031)	(0.026)	(0.058)
Observations	7731	5121	4660	5682	9367	11467	7731
Rec. 4th Sem. GPA	0.032	0.085	0.015	0.015	0.024	0.024	0.011
	(0.056)	(0.075)	(0.070)	(0.069)	(0.053)	(0.052)	(0.108)
Observations	4756	3097	2769	3443	5850	7316	4756
Rec. 6th Sem. GPA	0.010	0.015	-0.125	-0.071	0.007	0.006	-0.166
	(0.057)	(0.079)	(0.077)	(0.070)	(0.051)	(0.056)	(0.105)
Observations	3827	2391	2201	2751	4703	5904	3827
Rec. 8th Sem. GPA	-0.054	-0.038	-0.100	-0.067	-0.052	-0.066	-0.098
	(0.060)	(0.084)	(0.076)	(0.067)	(0.059)	(0.055)	(0.113)
Observations	3260	1916	1860	2336	4012	5052	3260
4 Year Graduation Rate	-0.018	-0.042	-0.011	-0.015	-0.016	-0.014	0.009
	(0.024)	(0.026)	(0.026)	(0.025)	(0.022)	(0.019)	(0.037)
Observations	5446	2849	3325	4036	6586	8053	5446
5 Year Graduation Rate	-0.003	-0.092*	0.016	0.002	-0.011	-0.039	0.040
	(0.041)	(0.048)	(0.047)	(0.042)	(0.037)	(0.034)	(0.067)
Observations	4697	2108	2863	3485	5696	6969	4697
6 Year Graduation Rate	0.034	-0.031	0.058	0.050	0.015	-0.029	0.091
	(0.047)	(0.061)	(0.060)	(0.052)	(0.044)	(0.039)	(0.085)

Observations	4177	1594	2545	3099	5070	6176	4177

Notes: Control variables include gender, race, and SAT score, high school rank, and year dummies

Table 4A

Robustness of Findings for UTSA: Changes to Bandwidth and Specification

Specification	Baseline (From tables)	Baseline (w/ controls)	Linear	Linear	Linear	Linear	Polynomial
Bandwidth	0.6	0.6	0.4	0.5	0.7	0.8	0.6
Second Sem Persistence	-0.015	-0.014	-0.027	-0.004	-0.006	-0.002	-0.037
	(0.017)	(0.025)	(0.025)	(0.026)	(0.017)	(0.015)	(0.042)
Observations	8421	5477	5055	5576	9654	12031	8421
2nd Semester GPA	0.149**	0.167**	0.090	0.152	0.080	0.088	0.126
	(0.068)	(0.073)	(0.107)	(0.101)	(0.066)	(0.055)	(0.146)
Observations	7696	4985	4620	5113	8788	10968	7696
Second Sem Improvement	0.101**	0.117**	0.048	0.078	0.060*	0.075**	0.043
	(0.039)	(0.048)	(0.056)	(0.048)	(0.035)	(0.030)	(0.076)
Observations	7696	4985	4620	5113	8788	10968	7696
Third Semester Persistence	-0.060*	-0.066*	-0.050	-0.025	-0.067**	-0.061**	0.028
	(0.034)	(0.036)	(0.058)	(0.052)	(0.033)	(0.030)	(0.079)
Observations	7169	4327	4365	4784	8262	10215	7169
Rec. 4th Sem. GPA	0.115	0.165	0.168	0.063	0.097	0.087	0.157
	(0.075)	(0.117)	(0.125)	(0.111)	(0.078)	(0.069)	(0.183)
Observations	4524	2767	2717	3002	5148	6375	4524
Rec. 6th Sem. GPA	0.032	0.177	0.211	0.183	0.017	0.072	0.314
	(0.090)	(0.115)	(0.130)	(0.124)	(0.085)	(0.084)	(0.198)
Observations	2941	1718	1771	1951	3360	4195	2941
Rec. 8th Sem. GPA	-0.142	-0.206	-0.036	0.007	-0.040	-0.003	-0.075
	(0.117)	(0.143)	(0.163)	(0.155)	(0.104)	(0.092)	(0.258)
Observations	2245	1297	1349	1499	2567	3205	2245
4 Year Graduation Rate	-0.002	0.008	-0.008	0.012	-0.003	0.002	0.020
	(0.014)	(0.014)	(0.021)	(0.021)	(0.013)	(0.012)	(0.029)
Observations	5527	2907	3433	3758	6394	7823	5527
5 Year Graduation Rate	-0.020	-0.023	-0.040	-0.021	-0.027	-0.014	-0.052
	(0.026)	(0.040)	(0.039)	(0.038)	(0.026)	(0.022)	(0.057)
Observations	4911	2386	3052	3350	5660	6908	4911
6 Year Graduation Rate	-0.022	0.024	-0.010	-0.004	-0.027	-0.024	-0.006
	(0.032)	(0.044)	(0.053)	(0.046)	(0.031)	(0.026)	(0.074)

Observations	4284	1834	2656	2926	4941	6001	4284

Notes: Control variables include gender, race, and SAT score, high school rank, and year dummies