

# Lack of Evidence?: Academic Probation Does Not Affect Student Dropout and Subsequent Performance

Revisiting the Ability, Gender, and Performance Standards: Evidence from Academic Probation (Lindo, Sanders, and Oreopoulos 2010)

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## Abstract

Many universities use academic probation as a wake-up call to ensure currently enrolled students to achieve minimum academic standards. This paper examines the causal impact on first-year students' responses in a Canadian university after being placed on academic probation in a sharp regression discontinuity design. With adjusted bandwidth, the results do not suggest that placing first year students on academic probation affects the dropout decision, subsequent annual GPA and graduation. While there are heterogeneous responses across students' highschool performance, gender, first language towards academic probation.

**Keywords:** Regression Discontinuity Design, Bandwidth, Academic Probation, Student Performance, P-value, Causality

## 1 Introduction

First-year students usually hold positive expectations after entering the university (McGrath and Burd 2012). Despite their high expectations, some students fail to achieve the minimum academic standards and are placed into academic probation. Academic probation serves as a wake-up call for students whose grade point average (GPA) is below a certain threshold and can lead to escalating penalties such as suspensions. Therefore, placing students on academic probation is equivalent to setting a minimum standard for their future academic performance (Lindo, Sanders, and Oreopoulos 2010), while previous studies implied that students may react quite differently to academic probation (e.g., dropout, increase academic performance, etc.)(Bénabou and Tirole 2000).

This paper examines the causal impact on first-year university students after being placed on academic probation by exploiting the discontinuous probation GPA cutoff in a sharp regression discontinuity design (RDD). The data comes from a large Canadian university with three individual campuses. It aims to replicate main findings in "Ability, Gender, and Performance Standards: Evidence from Academic Probation."<sup>1</sup> (Lindo, Sanders, and Oreopoulos 2010) with adjustment on the bandwidth (i.e., student within certain grade point average of the academic probation cutoff). After applying the adjusted bandwidth, the results are NOT consistent with Lindo's findings that being placed on probation at the end of the first year increases the student dropout, improves the GPAs of the remaining students and negatively affects graduation rates. While students with different gender, highschool academic performance or first language react differently to academic probation. Furthermore, I also find heterogeneous responses towards academic probation across campus that is not elaborated in the original paper.

The rest of this paper is organized as follows: In Data section (Section 2), I would first explain the domain background about the academic probation. Next, I introduce the data used in the original paper. And then, I would describe the Quasi-experiment design rationale and raise concerns about the bandwidth used in the

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<sup>1</sup>Original paper available at: <https://www.aeaweb.org/articles?id=10.1257/app.2.2.95>

original paper. In Model section (Section 3), I elaborate on the sharp RDD, address its assumptions and propose the model used in this study. In Results section (Section 4), I show the impact of academic probation on student dropout and subsequent academic performance with the adjusted bandwidth. In Discussion section (Section 5), I would first comment on the study results, and then elaborate on the causality of this quasi-experiment, address internal and external validity regarding the campus variation. I would also discuss potential bias in this experiment. Finally, I conclude and suggest future directions of this study.<sup>2</sup>

## 2 Data

The data comes from a large Canadian university with three individual campuses: one central campus (Campus 1) and two smaller satellite campuses (Campus 2 and Campus 3) from 1996 to 2005. I analyzed it using R (R Core Team 2020), and packages `tidyverse` (Wickham et al. 2019), `here` (Müller 2020), `rdrobust` (Calonico et al. 2021), `rdd` (Dimmery 2016), `rdpower` (Cattaneo, Titiunik, and Vazquez-Bare 2020), `haven` (Wickham and Miller 2020). I used packages `bookdown` (Xie 2016), `kableExtra` (Zhu 2020), `finalfit` (Harrison, Drake, and Ots 2020), `modelsummary` (Arel-Bundock 2021), `broom` (Robinson, Hayes, and Couch 2020), `ggpubr` (Kassambara 2020) to format the document and referenced `Impact Evaluation in Practice` (Gertler et al. 2016) to evaluate this experiment. I used `Shiny` (Chang et al. 2021) for enhancement to display interactive model results (Discussion Section 5.5).

### 2.1 About Academic Probation

The principle of academic probation in this university is simple: if a student’s grade point average (GPA) is below a certain threshold, the student is placed on academic probation. At Campus 1 and Campus 2, students with a cumulative GPA below 1.5 grade points are placed on academic probation. Campus 3 has a GPA cutoff at 1.6 grade points. Students with GPA exactly at the probation cutoff are considered in good academic standing. The following histograms on student highschool grade and attempted course credit in first year suggest that students on academic probation generally have lower highschool grades (Figure 1), and attempt less courses for credits in the first year<sup>3</sup> (Figure 2).

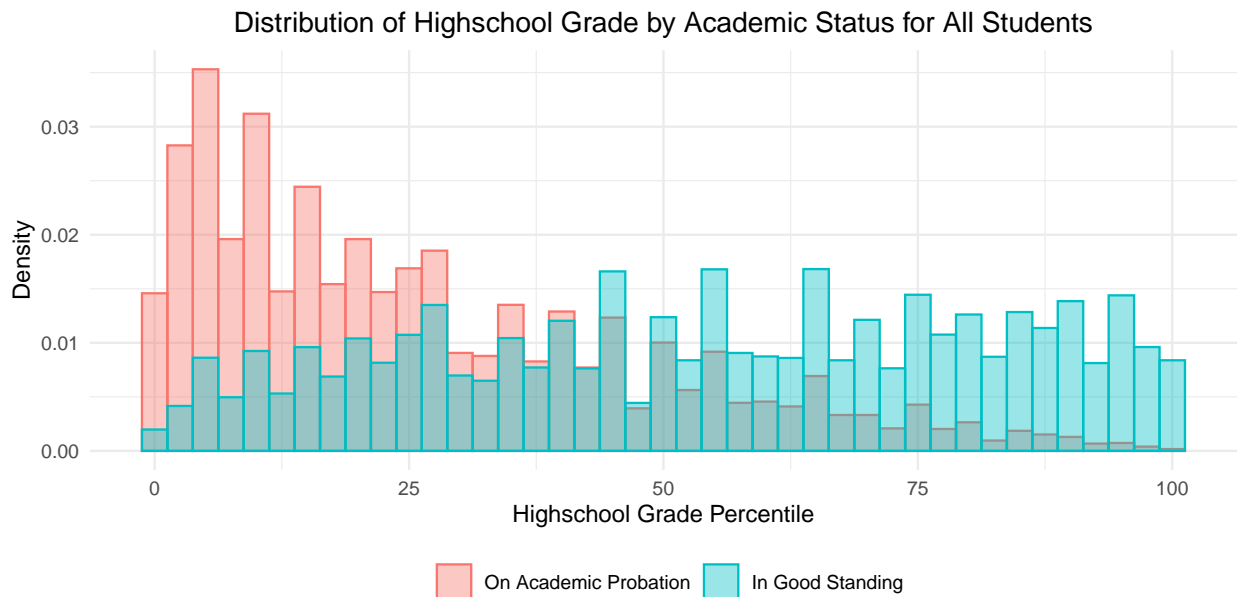


Figure 1: Distribution of Highschool Grade by Academic Status for All Students

<sup>2</sup>Codes and data are available at the GitHub repo: [https://github.com/honn-ishinn/RDD\\_academic\\_probation](https://github.com/honn-ishinn/RDD_academic_probation).

<sup>3</sup>Each semester course counts as 0.5 credit, each year course counts as 1 credit

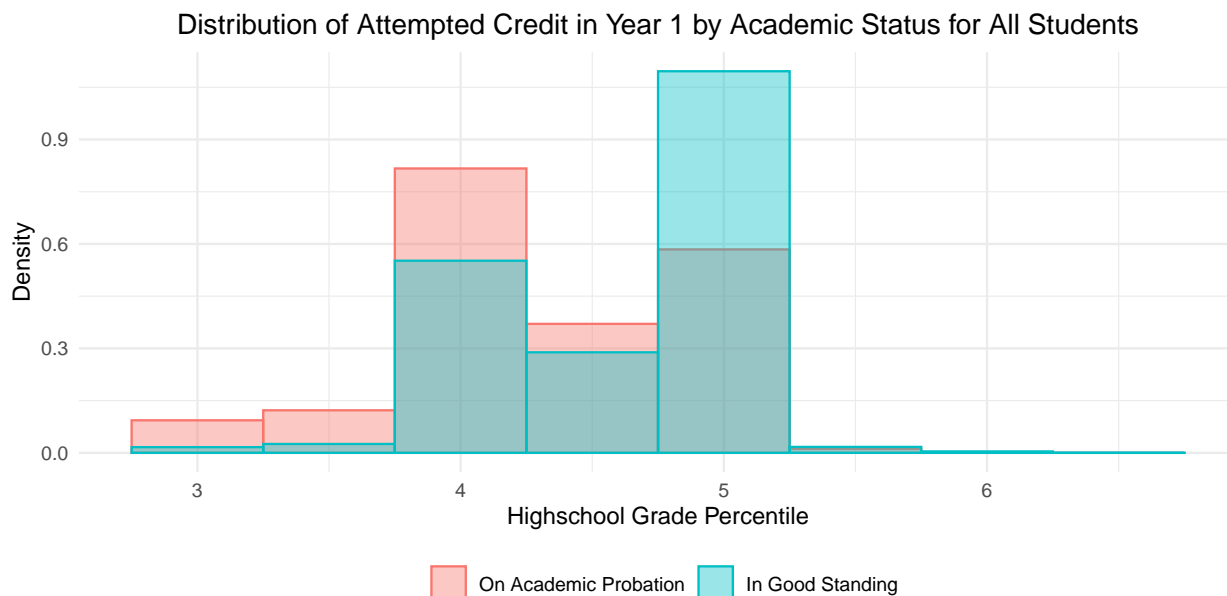


Figure 2: Distribution of Attempted Credit in Year 1 by Academic Status for All Students

Since many first-year courses span the entire year, students' academic standings are evaluated at the end of first scholastic year. Academic standings are evaluated at the end of every subsequent scholastic year and summer term at Campus 1 and Campus 2, and end of every subsequent term at Campus 3<sup>4</sup>.

Students on academic probation will be suspended in subsequent sessions if their grades do not improve. At all campuses, students on probation can avoid suspension and return to good academic standing by improving their cumulative GPA up to the cutoff. Students who fail to sufficiently improve their grades are suspended for one full academic year. If suspended students return to the university and again fail to sufficiently improve their grades, they can be suspended for three years. A third failure to meet the GPA requirement can lead to permanent suspension from all campuses. Students will be notified after being placed on academic probation. A sample letter sent to students at Campus 2 is in Appendix (Appendix A).

## 2.2 Original Data

The data used in the original paper includes administrative information of students in a large Canadian university as mentioned above. It covers student observations in a nine-year period from 1996 to 2005 and has cleaned the student sample in following aspects for the purpose of this experiment<sup>5</sup>:

1. Restrict students who entered the university before 2004 so that students can be potentially observed for two years.
2. Omit students with missing data for any variables of interest, particularly high school grades (84% of the sample).
3. Restrict students entering the university between age 17 and 21 (99% of the remaining sample).
4. Restrict students having their academic standing evaluated at the end of Year 1 (98% of the remaining sample).

<sup>4</sup>Students also must attempt a minimum number of credits before being evaluated. The data used in the original paper omit all students who have not been evaluated by the end on first year. Potential bias issues are elaborated in Discussion section

<sup>5</sup>Potential bias issues about data cleaning in the original paper are elaborated in Discussion section

Table 1: Summary Statistics of Observable Characteristics and Outcomes of All Students

Description		All Students
Characteristics		
		N(%) = 44362 (100.0)
Gender	Male	16981 (38.3)
	Female	27381 (61.7)
Birth Place	North America	38633 (87.1)
	Asia	3763 (8.5)
	Other	1966 (4.4)
Study Campus	Campus 1	25915 (58.4)
	Campus 2	7695 (17.3)
	Campus 3	10752 (24.2)
First Language	English	31662 (71.7)
	Other	12469 (28.3)
		Mean (SD)
Highschool Grade Percentile		50.17 (28.86)
Credits Attempted in First Year		4.57 (0.51)
Age at Entry		18.67 (0.74)
Outcomes		
		N(%) = 44362 (100.0)
On Probation After 1st Year	Yes	7106 (16.0)
	No	37256 (84.0)
Ever On Probation	Yes	8711 (19.6)
	No	35651 (80.4)
Left University After 1st Evaluation	Yes	2175 (4.9)
	No	42187 (95.1)
Ever Suspended	Yes	3562 (8.0)
	No	40800 (92.0)
Graduated by Year 4	Yes	13407 (44.7)
	No	16610 (55.3)
Graduated by Year 5	Yes	16594 (67.5)
	No	7987 (32.5)
Graduated by Year 6	Yes	14880 (75.3)
	No	4877 (24.7)
		Mean (SD)
First Year GPA		2.44 (0.89)
Distance from Cutoff in 1st Year		0.91 (0.90)
Second Year GPA		2.55 (0.83)
Distance from Cutoff in 2nd Year		1.03 (0.84)

<sup>1</sup> For all characteristics and outcomes except graduation rates and distance from cutoff in 2nd year. The entire dataset consists of 44362 students. Graduation rate samples are 30017 for Year 4, 24581 for Year 5, 19757 for Year 6. 38576 students have GPA observed in 2nd Year

After the data cleaning, the original data includes a total of 44362 observations and Table 1 shows the summary statistics of student observable characteristics and outcomes such as gender, age, birth place, study campus, first language, attempted course credit<sup>6</sup>, registration status, GPA, academic standing, high school performance, and graduation status. Since the probation cutoff among campus is different (1.5 GPA in Campus 1 and 2, 1.6 GPA in Campus 3), the data also includes the variable of distance from the campus probation cutoff. Instead of the absolute GPA, the distance from cutoff variable will be used as the forcing variable in the regression discontinuity design which will be discussed in the following section.

## 2.3 Quasi-Experiment and About Bandwidth Selection

### 2.3.1 Regression Discontinuity Design

Instead of a randomized experiment, this study belongs to the quasi-experiment because students' academic statuses are not randomly assigned by the university administration. As the probation cutoff score is clearly defined and the GPAs affect students' academic statuses, the regression discontinuity design (RDD) is the method used to evaluate the probation impact. Therefore, the cutoff rule assigns students barely below the probation cutoff (On probation) into the treatment group and those barely above the probation cutoff (In good standing) into the comparison group to estimate impact on first-year university students after being placed on academic probation.

### 2.3.2 Concerns about Bandwidth Selection

In this study, since the RDD only provides the most accurate estimates around the probation cutoff where treatment and comparison are most similar (Gertler et al. 2016), it is critical to determine the bandwidth(i.e., students within certain grade points of the probation cutoff score) to maintain the balance of observed characteristics of students around the probation cutoff. In Lindo's original paper, they choose the bandwidth of 0.6 GPA and the following table (Table 2) shows the summary statistics of student observable characteristics within 0.6 GPA.

Table 2: Summary Statistics of Students Within 0.6 GPA of Probation Cutoff

Description		In Good Standing	On Academic Probation
		N(%) = 8142 (65.1)	N(%) = 4365 (34.9)
Gender	Male	3000 (36.8)	1688 (38.7)
	Female	5142 (63.2)	2677 (61.3)
Birth Place	North America	7151 (87.8)	3734 (85.5)
	Asia	622 (7.6)	429 (9.8)
	Other	369 (4.5)	202 (4.6)
Study Campus	Campus 1	4088 (50.2)	1896 (43.4)
	Campus 2	1695 (20.8)	929 (21.3)
	Campus 3	2359 (29.0)	1540 (35.3)
First Language	English	5947 (73.4)	3041 (69.9)
	Other	2156 (26.6)	1310 (30.1)
		Mean (SD)	Mean (SD)
Highschool Grade Percentile		35.80 (23.55)	28.78 (22.03)
Credits Attempted in First Year		4.46 (0.52)	4.37 (0.55)
Age at Entry		18.71 (0.73)	18.74 (0.74)

According to Cohn et al. (2004), highschool grade is one of the key determinants of university academic success. Thus, highschool grades could somehow reveal students' study potential in the university, so it is preferable to balance student highschool performance to obtain a more accurate estimate of academic

<sup>6</sup>This Canadian university requires at least 20 course credits to graduate.

probation. However, the t-test (Table 3) conducted on highschool grade percentile suggests a large difference on highschool performance between student observations in good standing and on academic probation within Lindo’s 0.6 GPA bandwidth. In addition, the study on the course load on academic success (Szafran 2001) implies that course credit taken by students could reflect student academic ability. Therefore, another t-test (Table 4) is conducted on total course credits attempted<sup>7</sup> in Year 1 between students in good standing and on probation. The result suggests a difference in the course workload between good standing and probation students within Lindo’s 0.6 GPA bandwidth. As a result, the bandwidth that Lindo used in the original paper may include students with different academic potentials, reducing the local estimation accuracy of placing first-year students on academic probation.

Table 3: Two Sided T-test on Student Highschool Grade Percentile within 0.6 GPA cutoff

On Probation	In Good Standing	P-value	95% CI Low	95% CI High	Method
28.78	35.8	9.713e-61	-7.843	-6.183	Welch Two Sample t-test

Table 4: Two Sided T-test on Student Credits Attempted in Year 1 within 0.6 GPA cutoff

On Probation	In Good Standing	P-value	95% CI Low	95% CI High	Method
4.37	4.458	1.462e-18	-0.1086	-0.06907	Welch Two Sample t-test

The following table (Table 5) shows the grading theme of this Canadian university<sup>8</sup>. By applying Lindo’s bandwidth of 0.6 GPA, observations barely above the probation cutoff roughly covers students within 60-66 average grade percentage (1.5-2.1 GPA in Campus 1 and 2, 1.6-2.2 GPA in Campus 3), and observations barely below the probation cutoff roughly covers students within 53-59 average grade percentage (0.9-1.5 GPA in Campus 1 and 2, 1.0-1.6 GPA in Campus 3). By converting grade point value into grade percentage, it might become more obvious that there exists academic performance difference between students in good standing with 66 average grade percentage and students on probation with 53 average grade percentage. Therefore, I would argue that the bandwidth used in Lindo’s is too wide to maintain similar characteristics, particularly academic potentials, between the probation and good standing students.

Table 5: Grading Scheme of the University

Grade	Grade Point Value	Grade Percentage	Definition
A+	4.0	90-100	Excellent
A	4.0	85-89	
A-	3.7	80-84	
B+	3.3	77-79	Good
B	3.0	73-76	
B-	2.7	70-72	
C+	2.3	67-69	Adequate
C	2.0	63-66	
C-	1.7	60-62	
D+	1.3	57-59	Marginal
D	1.0	53-56	
D-	0.7	50-52	
F	0.0	0-49	Inadequate; no credit obtained

<sup>7</sup>Failing a course will not earn course credit but count as an attempted credit

<sup>8</sup>This is the current grading theme of this university as of 2021. The grading theme between 1996 and 2005 might be different and could not be retrieved on the university website. While the current grading theme may still serve as a reference of this study

As a result, I would adjust the bandwidth to:

1. Balance characteristics between good standing and probation students within the bandwidth.
2. Maintain a sufficient number of observations to obtain sufficient statistical power.

Table 6: Summary Statistics of Students Within 0.2 GPA of Probation Cutoff

Description		In Good Standing	On Academic Probation
		N(%) = 2361 (57.5)	N(%) = 1745 (42.5)
Gender	Male	875 (37.1)	636 (36.4)
	Female	1486 (62.9)	1109 (63.6)
Birth Place	North America	2061 (87.3)	1522 (87.2)
	Asia	191 (8.1)	141 (8.1)
	Other	109 (4.6)	82 (4.7)
Study Campus	Campus 1	1099 (46.5)	782 (44.8)
	Campus 2	524 (22.2)	361 (20.7)
	Campus 3	738 (31.3)	602 (34.5)
First Language	English	1720 (73.3)	1205 (69.4)
	Other	628 (26.7)	532 (30.6)
Highschool Grade Percentile		Mean (SD)	Mean (SD)
Credits Attempted in First Year		32.46 (22.80)	30.82 (22.41)
Age at Entry		4.40 (0.52)	4.40 (0.55)
		18.72 (0.74)	18.72 (0.75)

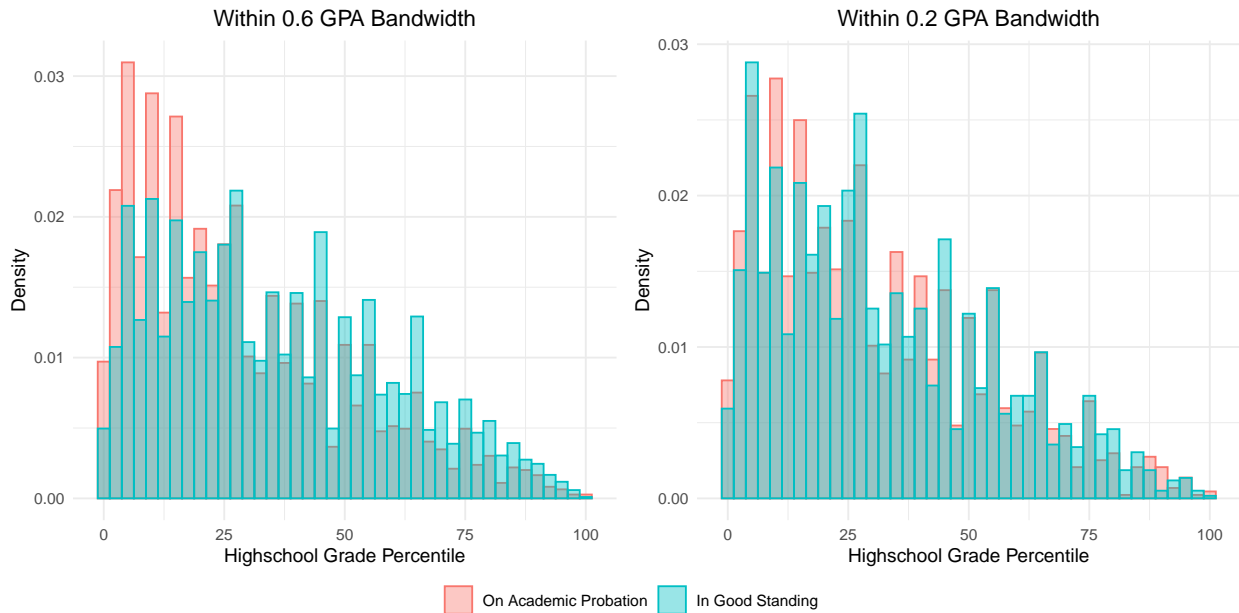


Figure 3: Distribution of Highschool Grade Within Certain GPA Bandwidth

Since the probation cutoff GPA lies between “adequate” C- of 1.7 GPA and “marginal” D+ of 1.3 GPA, I adjust the bandwidth to 0.2 GPA to reduce the academic performance difference. Table 6 shows the summary statistics of 4106 student observable characteristics within 0.2 GPA. Even though the t-test (Table 7) on highschool grade percentile still suggests difference on highschool performance, the estimated highschool grade percentile difference is much less than those within 0.6 bandwidth. Many probation students with low highschool grade are excluded after applying the narrower 0.2 GPA bandwidth as shown in the above histogram (Figure 3). Besides, the t-test (Table 8) on course credit does not show a significant difference in course load within 0.2 bandwidth, so the observed characteristics become more balanced.

Table 7: Two Sided T-test on Student Highschool Grade Percentile within 0.2 GPA cutoff

On Probation	In Good Standing	P-value	95% CI Low	95% CI High	Method
30.82	32.46	0.0219	-3.032	-0.2369	Welch Two Sample t-test

Table 8: Two Sided T-test on Student Credits Attempted in Year 1 within 0.2 GPA cutoff

On Probation	In Good Standing	P-value	95% CI Low	95% CI High	Method
4.401	4.404	0.8692	-0.03591	0.03035	Welch Two Sample t-test

The power of a test is the probability that the test will reject the test null hypothesis to detect a correct alternative hypothesis (Greenland et al. 2016). In this study, as the length of the bandwidth increases, more students are included within the bandwidth. The increase in the number of students raises the power to detect the impact on placing students on probation so that the impact estimation is less likely to happen by chance rather than by the probation cutoff rule. Therefore, I use the `rdpower`(Cattaneo, Titiunik, and Vazquez-Bare 2020) package to calculate the sufficient sample size required (i.e., effect size) to detect the probation effect on (1) Student dropout, (2) Second year GPA and (3) Graduation rate by Year 4. The result as shown below (Table 9) suggests that the bandwidth of 0.2 GPA with 4106 students (1745 on probation, 2361 in good standing) could raise sufficient statistical power. Further adjustment on the bandwidth might either unbalance student characteristics (Increase bandwidth) or decrease the power of the study (Decrease bandwidth). So I would apply the bandwidth of 0.2 GPA to examine the academic probation impact in the following sessions.

Table 9: Sample Required to Raise Sufficient Power

Interest	Total Student	On Probation	In Goodstanding
Dropout	894	359	535
GPA in Year 2	1094	448	646
Graduation by Year 4	1375	625	750

<sup>1</sup> The significance level is 0.05 and desired power is 0.8.

### 3 Model

#### 3.1 Test on Regression Discontinuity Design Assumptions

Before applying the regression discontinuity design in this study, it is important to test its assumptions to ensure the constructed RDD model accurately represent the impact of academic probation on first-year students. Several assumptions of RDD are:

1. The cutoff is clearly defined, unique (Gertler et al. 2016): This Canadian university clearly defined the academic probation rule (1.5 GPA in Campus 1 and 2, 1.6 GPA in Campus 3). There is also no other academic status (Other than in good standing and on probation) defined around the probation cutoff score, so this assumption is satisfied.



2. The score of the individual free of manipulation (Gertler et al. 2016): The university Code of Behavior on Academic Matters ensures that student GPA cannot be manipulated, so this assumption is satisfied.
3. The forcing variable should be continuous (Alexander 2021): as mentioned in Data Section 2.2, this study uses student GPA distance from cutoff as the forcing variable. Since the GPA is a continuous variable, the GPA distance from cutoff is also continuous so this assumption is satisfied.
4. The treatment and comparison units are most similar (Gertler et al. 2016): as mentioned in Data Section 2.3.2, I would apply the adjusted bandwidth to balance the characteristics between students on probation barely below the cutoff and in good standing barely above the cutoff.

Since the academic probation cutoff rule is known, one may question that students barely below the probation cutoff would study harder to avoid being placed on academic probation. However, the survey conducted in Lindo’s paper suggests that first year students are generally less familiar with university policies to know exact GPA required to avoid academic probation. And Lindo also finds no evidence that students’ grades are related to their knowledge about academic probation (Lindo, Sanders, and Oreopoulos 2010). So first year students are NOT likely to “play with” the university probation policy to avoid academic probation. The following figure (Figure 4) shows the distribution of the GPA distance from probation cutoff of all students. There is a smooth increase on the frequency distribution of the student GPA until reaching students’ average GPA (GPA distance from probation around 1) and there is no obvious jump on either side of the probation cutoff. So students on either side of the probation cutoff is balanced as suggested in Data Section 2.3.2.

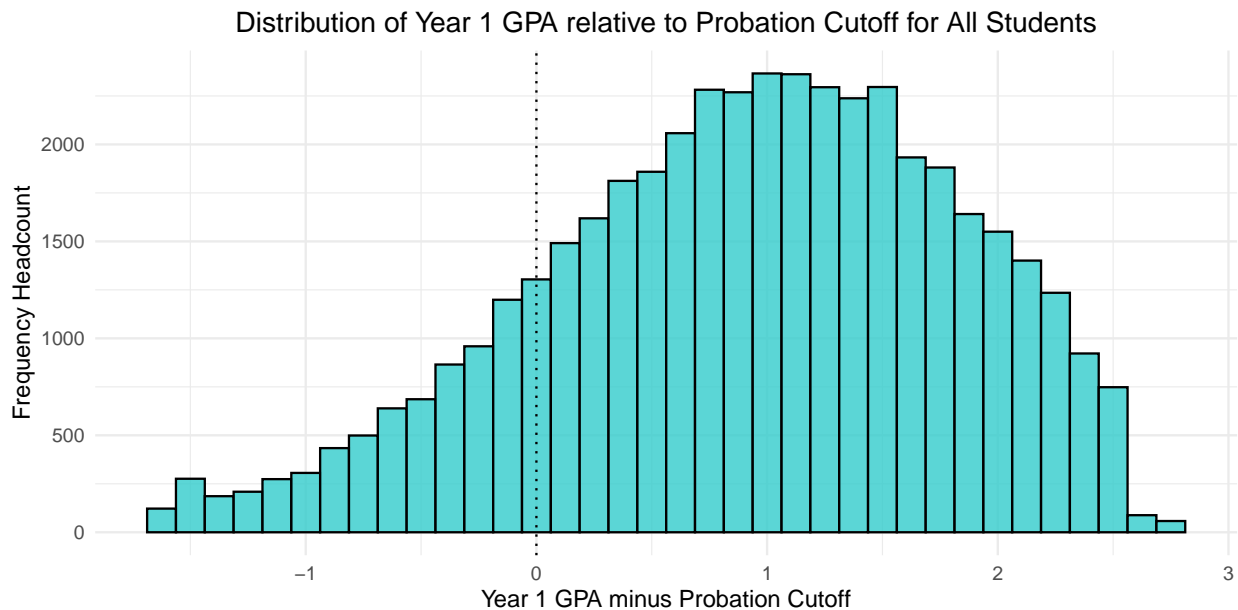


Figure 4: Distribution of Year 1 GPA relative to Probation Cutoff for All Students

## 3.2 Sharp RDD Model

### 3.2.1 Model Background

The university policy ensures that all first year students below the probation cutoff are on academic probation and those above the cutoff are in good standing.<sup>9</sup> So the discontinuity around the cutoff is “sharp”.

<sup>9</sup>The original data has university administrative errors in data reporting that falsely place students either above cutoff on probation or below cutoff in good standing (98 out of 44362 student observations). These dirty data are removed from this study.

By placing students on academic probation, the university informs these students an urge to improve their academic performance to prevent further escalating penalties such as suspension. According to Bénabou and Tirole’s model of agents’ responses to a performance standard (Bénabou and Tirole 2000), the probation policy as a negative incentive may result in the following outcomes:

1. Discourage some students to continue their study in the university, leading to an increasing chances of student dropout.
2. Encourage the rest of students to improve their GPA, leading to an improve of GPA in the second year.

Since students on probation status are allowed to take limited course credits<sup>10</sup>, unless students actively seek to earn credits in subsequent academic year (e.g., enroll in summer course, taking more courses after going back to good standing), this policy would also:

3. Postpone the graduation, leading to an decreasing chances of graduating within certain time periods.

In addition, previous studies have suggested that:

- There is gender difference in academic performance (Dayioğlu and Türüt-Aşık 2007) and females appears to be more vulnerable to internal distress than males (Pomerantz, Altermatt, and Saxon 2002), so students with different gender may response quite differently after being placed on probation.
- Students with higher highschool grade are more likely to succeed in the university (Cohn et al. 2004). Even though some students with satisfactory highschool performance are unfortunately placed on academic probation (Possibly due to lack of university adaptation), they generally hold higher study potential than those with relatively poor highschool performance, triggering faster recovery from academic probation. So students with different highschool performance may response differently towards probation.
- The level of English language proficiency is important to academic success (Graham 1987). Students whose first language are not English may hold different level of English proficiency than English native speaking students. Similar to students with high highschool performance, English native speaking students may recover faster from academic probation. So students with different first language may also response differently towards probation.

### 3.2.2 Model Construction

Taking all of the above into consideration, I propose the following model to evaluate the impact on first year students after being placed on academic probation:

$$Y_i = \beta_0 \text{Probation}_i + f(\text{Cutoff Distance}_i) + \alpha_1 \text{Gender}_i + \alpha_2 \text{HighSchool}_i + \alpha_3 \text{Language}_i + \epsilon_i$$

where

- $Y_i$  is first year student outcomes of interest for student  $i$ , which are (1) Probability of dropout after the first academic year, (2) Annual GPA in the second academic year, and (3) Probability of graduating by the fourth year after entering the university.
- $\text{Probation}_i$  is an indicator variable to show whether the student  $i$  is placed on academic probation or not in the first year. And its coefficient  $\beta_0$  is the estimate of impact on first year students after being placed on academic probation that we are primarily interested in.
- $f(\text{Cutoff Distance}_i)$  is the function to represent the student  $i$ ’s first year GPA distance from the cutoff. Since the first order polynomial is used during the power analysis to determine required student samples (Data Section 2.3.2), it will also be applied in building the sharp RDD model<sup>11</sup>.

<sup>10</sup>This university has the up-to-date policy regarding to credit restrictions on probation students. However, this policy varies across campuses and the rule during the data collected period (1996-2005) could not be retrieved from the university website.

<sup>11</sup>Adjusting the order of distance from cutoff function till fourth order does not affect the results. Lindo’s original paper also used first order polynomial on distance from the cutoff to estimate probation outcomes.

- Gender<sub>*i*</sub> is an indicator variable to show whether the student *i* is male or female. Its coefficient  $\alpha_1$  is the estimate of gender difference in response to academic probation.
- HighSchool<sub>*i*</sub> is an indicator variable to show whether the student *i* has a satisfactory highschool performance (Highschool Grade Percentile > 50) or a relatively poor highschool performance (Highschool Grade Percentile ≤ 50). Its coefficient  $\alpha_2$  is the estimate of highschool performance difference in response to academic probation.
- Language<sub>*i*</sub> is an indicator variable to show whether the student *i*'s first language is English or other language. Its coefficient  $\alpha_3$  is the estimate of first language difference in response to academic probation.

Since the dropout decision of an individual student is whether leaving the university or not, it is a dichotomous variable. Therefore, I would use the logistic regression to estimate the probation impact on probability of student dropout. Similarly, the graduation decision of whether graduating by Year 4 or not is also a dichotomous variable. So I would also use the logistic regression to estimate the probation impact on probability of student graduating by Year 4.

As the GPA is a continuous variable from 0.0 to 4.0, I would use the linear regression to estimate the probation impact on student annual GPA in the second academic year.

## 4 Results

Surprisingly, after restricting student samples within 0.2 probation cutoff GPA, the model results do not suggest significant academic probation impact on any student outcomes of interest (dropout, Year 2 GPA and graduation). This is inconsistent with Lindo's findings that there is significant academic probation impact on all outcomes of interest within 0.6 probation cutoff GPA.

### 4.1 Impact on Dropout

As mentioned in Model Section 3.2.2, logistic regression is used to estimate the probation impact on probability of student dropout.

$$Prob(\text{Dropout}_i) = \beta_0 \text{Probation}_i + f(\text{Cutoff Distance}_i) + \alpha_1 \text{Gender}_i + \alpha_2 \text{HighSchool}_i + \alpha_3 \text{Language}_i + \epsilon_i$$

In this model, the baseline characteristics of the first year students is (1) on academic probation, (2) GPA distance from the probation cutoff is 0, (3) female, (4) highschool grade below the average, (5) first language is English. The following table (Table 10) shows regression results of student samples within different GPA bandwidth (0.2 GPA, 0.3 GPA, 0.6 GPA, respectively). Within 0.2 GPA bandwidth, compared to students on academic probation, students in good standing have 0.711 times odds to leave the university, i.e., 28.9% decrease in the odds of leaving the university, while holding other baseline characteristics constant. **However**, the p-value of 0.223, which is greater than the widely defined 0.05 threshold, suggests that the first year dropout decision does not significantly differ between good standing students and probation students, holding other baseline characteristics constant. And this difference could also not be clearly detected around the probation cutoff as shown below (Figure 5). While within 0.6 GPA bandwidth used in Lindo's original paper, the results do suggest significant difference that students in good standing have 34.8% decrease in the odds of first year dropout, holding other baseline characteristics constant. Such difference is also significant within 0.3 GPA bandwidth.

Within 0.2 GPA bandwidth, there is significant difference on student dropout decision across first language: compared to English native speaking students, students whose first language are other languages have 54.5% decrease in the odds of first year dropout, holding other baseline characteristics constant. No other significant difference is found on student gender and highschool performance.

Table 10: Logistic Regression for the Impact of Academic Probation on Student Dropout

	0.2 GPA Bandwidth	0.3 GPA Bandwidth	0.6 GPA Bandwidth
Constant	0.080***	0.079***	0.075***
In Good Standing	0.176 (0.000)	0.145 (0.000)	0.101 (0.000)
f(Cutoff Distance)	0.711	0.627**	0.652***
	0.280 (0.223)	0.236 (0.048)	0.164 (0.009)
Gender Male	0.418	0.760	0.707
	1.240 (0.481)	0.702 (0.696)	0.244 (0.156)
Highschool Above Average	1.085	1.149	1.124
	0.145 (0.573)	0.120 (0.248)	0.085 (0.167)
First Language Not English	0.781	0.790	0.969
	0.186 (0.183)	0.154 (0.127)	0.101 (0.759)
	0.455***	0.498***	0.581***
	0.191 (0.000)	0.155 (0.000)	0.105 (0.000)
Num.Obs.	4085	6101	12454
AIC	1649.9	2385.7	4817.4
Log.Lik.	-818.948	-1186.829	-2402.720

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

<sup>1</sup> Odds Ratio in First Row. Standard Error of Log of Odds in Second Row.  
P-value in Parentheses

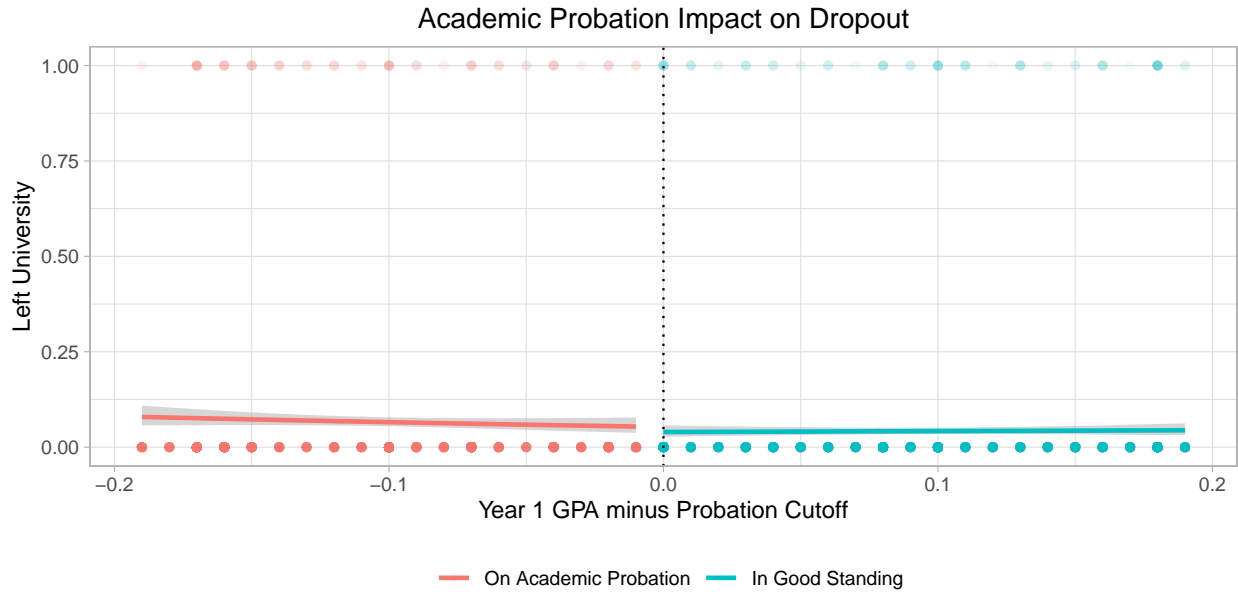


Figure 5: Academic Probation Impact on Dropout

## 4.2 Impact on Second Year Annual GPA

As mentioned in Model Section 3.2.2, linear regression is used to estimate the probation impact on student second year annual GPA.

$$\text{GPAYear2}_i = \beta_0 \text{Probation}_i + f(\text{Cutoff Distance}_i) + \alpha_1 \text{Gender}_i + \alpha_2 \text{HighSchool}_i + \alpha_3 \text{Language}_i + \epsilon_i$$

The model baseline characteristics are the same as mentioned in dropout Section 4.1. The following table (Table 11) shows regression results of student samples within different GPA bandwidth (0.2 GPA, 0.3 GPA, 0.6 GPA, respectively). Within 0.2 GPA bandwidth, compared to students on academic probation, students in good standing earn 0.055 less GPA than those on academic probation in the second year, while holding other baseline characteristics constant. **However**, the p-value of 0.245 suggests that the first year dropout decision does not significantly differ between good standing students and probation students, holding other baseline characteristics constant. And this difference could also not be clearly detected around the probation cutoff as shown below (Figure 6). While within 0.6 GPA bandwidth used in Lindo’s original paper, the results do suggest significant difference that students in good standing earn 0.145 GPA less than students on probation, holding other baseline characteristics constant. Such difference is also significant within 0.3 GPA bandwidth.

Within 0.2 GPA bandwidth, there is significant difference on student second year GPA across gender and highschool performance. Compared to female students, male students earn 0.120 less annual GPA in the second year, holding other baseline characteristics constant. Compared to students with relatively poor highschool academic performance, students with satisfactory highschool academic performance earn 0.099 more annual GPA in the second year, holding other baseline characteristics constant. No other significant difference is found on student first language.

Table 11: Linear Regression for the Impact of Academic Probation on Student Year 2 GPA

	0.2 GPA Bandwidth	0.3 GPA Bandwidth	0.6 GPA Bandwidth
Constant	1.987*** 0.031 (0.000)	2.013*** 0.025 (0.000)	2.046*** 0.017 (0.000)
In Good Standing	-0.055 0.047 (0.245)	-0.120*** 0.039 (0.002)	-0.145*** 0.027 (0.000)
f(Cutoff Distance)	0.021 0.206 (0.918)	0.446*** 0.114 (0.000)	0.553*** 0.039 (0.000)
Gender Male	-0.120*** 0.025 (0.000)	-0.104*** 0.020 (0.000)	-0.136*** 0.014 (0.000)
Highschool Above Average	0.099*** 0.029 (0.001)	0.112*** 0.023 (0.000)	0.097*** 0.015 (0.000)
First Language Not English	-0.047* 0.026 (0.077)	-0.015 0.022 (0.473)	-0.038** 0.015 (0.011)
Num.Obs.	3408	5118	10506
R2	0.013	0.014	0.049
R2 Adj.	0.011	0.013	0.048
AIC	7208.9	10799.1	21659.2
Log.Lik.	-3597.430	-5392.557	-10822.610
F	8.677	13.997	107.865

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

<sup>1</sup> Regression Coefficient in First Row. Standard Error in Second Row.

P-value in Parentheses

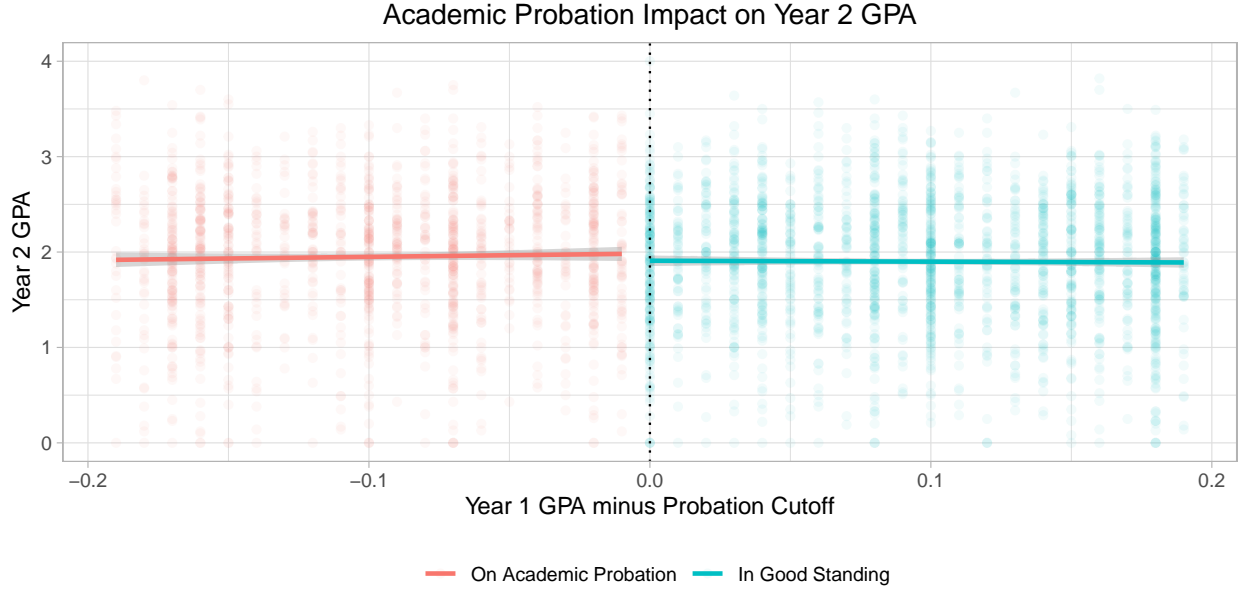


Figure 6: Academic Probation Impact on Year 2 GPA

### 4.3 Impact on Graduation

As mentioned in Model Section 3.2.2, logistic regression is used to estimate the probation impact on probability of student graduating by Year 4.

$$Prob(\text{Graduation}_i) = \beta_0 \text{Probation}_i + f(\text{Cutoff Distance}_i) + \alpha_1 \text{Gender}_i + \alpha_2 \text{HighSchool}_i + \alpha_3 \text{Language}_i + \epsilon_i$$

The model baseline characteristics are the same as mentioned in dropout Section 4.1. As shown in the following table (Table 12), within 0.2 GPA bandwidth, compared to students on academic probation, students in good standing have 26.8% increase in the odds of graduating by Year 4, while holding other baseline characteristics constant. **However**, the p-value of 0.161 suggests that the graduation does not significantly differ between good standing students and probation students, holding other baseline characteristics constant. And this difference could also not be clearly detected around the probation cutoff as shown (Figure 7). Within 0.3 GPA and 0.6 GPA bandwidth, the results also do not suggest difference on graduation between good standing students and probation students at 0.05 significance level, holding other baseline characteristics constant.

Within 0.2 GPA bandwidth, there is significant difference on student graduation across gender: compared to female students, male students have 49.9% decrease in the odds of graduating by Year 4, holding other baseline characteristics constant. No other significant difference is found on student highschool performance and first language.

Table 12: Logistic Regression for the Impact of Academic Probation on Student Graduation by Year 4

	0.2 GPA Bandwidth	0.3 GPA Bandwidth	0.6 GPA Bandwidth
Constant	0.386***	0.363***	0.357***
In Good Standing	0.110 (0.000)	0.091 (0.000)	0.065 (0.000)
f(Cutoff Distance)	1.268	1.267*	1.195*
	0.169 (0.161)	0.140 (0.091)	0.099 (0.073)
Gender Male	1.969	2.736**	3.432***
	0.737 (0.358)	0.414 (0.015)	0.144 (0.000)
Highschool Above Average	0.501***	0.540***	0.515***
	0.092 (0.000)	0.075 (0.000)	0.052 (0.000)
First Language Not English	1.086	1.061	1.053
	0.104 (0.431)	0.085 (0.488)	0.057 (0.368)
	1.063	1.117	1.141**
	0.095 (0.518)	0.078 (0.153)	0.054 (0.015)
Num.Obs.	2899	4307	8766
AIC	3307.3	4887.6	9984.9
Log.Lik.	-1647.655	-2437.810	-4986.436

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

<sup>1</sup> Odds Ratio in First Row. Standard Error of Log of Odds in Second Row. P-value in Parentheses

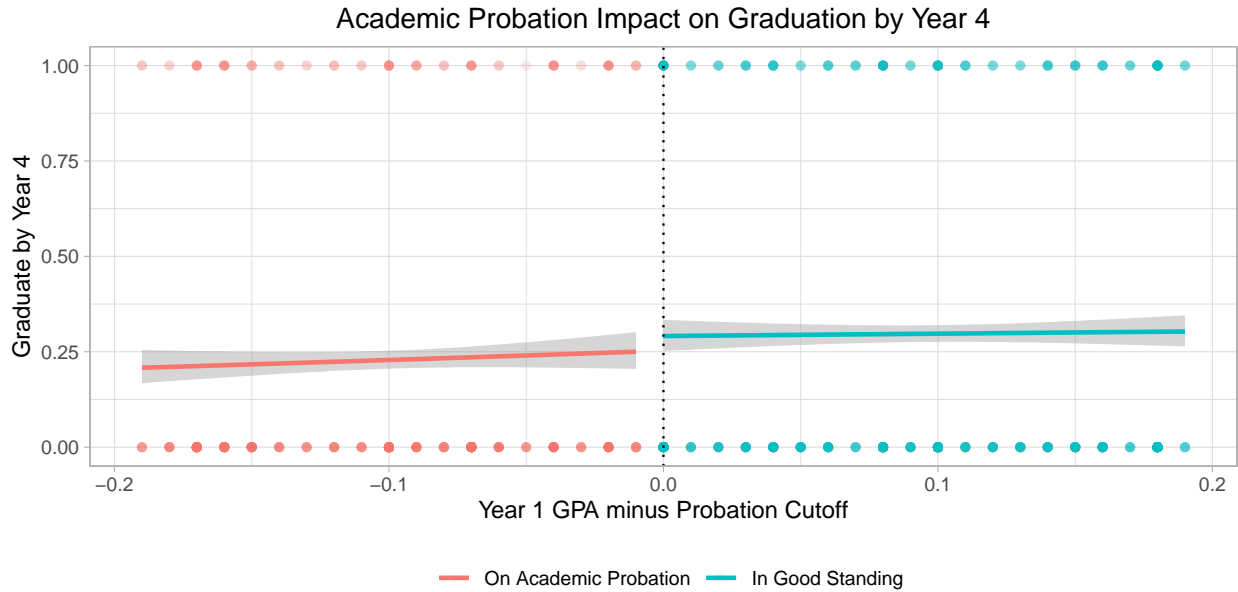


Figure 7: Academic Probation Impact on Graduation by Year 4

## 5 Discussion

### 5.1 P-value and RDD assumptions

Why does using student samples within the bandwidth of 0.6 GPA and even 0.3 GPA “has evidence” to suggest significant academic probation impact on student outcomes of interest (probability of immediate dropout, Year 2 annual GPA, probability of graduating by Year 4), while using student samples within the bandwidth of 0.2 GPA does not?

Since all result interpretations are based on p-values, reassessing the definition of p-value may help to explain the above inconsistent results. In simple common English, P-value means the probability that something checked wrong to happen. The lower p-value means a higher probability of something checked right to be true, and “is there an academic probation impact on first year student outcome” is the checkpoint in this study.

However, the p-value does not tell if the underlying assumptions of the checkpoint is correct or not. In the paper *Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations*, Greenland defines the p-value in a general view “as a statistical summary of the compatibility between the observed data and what we would predict or expect to see if we knew the entire statistical model (all the assumptions used to compute the P value) were correct”(Greenland et al. 2016). Therefore, reviewing RDD rationales and assumptions helps to draw correct interpretations from p-values.

In this study, the regression discontinuity design estimates academic probation impact on first year students by calculating the difference between treatment students on probation barely below the cutoff and comparison students in good standing barely above the cutoff. Its estimate is the most accurate where the treatment and comparison students are most similar and this estimate may not be generalized to students whose first year GPA are further away from the probation cutoff (Gertler et al. 2016).

According to the student summary statistics (Table 2) and t-test conducted on students highschool performance (Table 3) and credit attempted in the first year (Table 4) in Data Section 2.3.2, within the bandwidth of 0.6 GPA, students below the cutoff generally hold weaker academic potentials than those above the cutoff. And these academic differences also serve as key factors affecting student outcomes.

Even though Lindos’s original paper did test whether students share similar observable characteristics around the probation cutoff GPA in Results Section A (Lindo, Sanders, and Oreopoulos 2010), it failed to access student characteristics that are further away from the cutoff. It is unlikely that a student with 1.0 GPA is as similar as one with 2.0 GPA, while they are all included within Lindo’s bandwidth to estimate the impact of academic probation. As a result, using a wider bandwidth could violate the similarity assumption of RDD, and interpreting p-values from assumption violated models to seek “statistical significance” may become senseless.

### 5.2 Causal Inference, Internal Validity and External Validity

#### 5.2.1 Causal Inference and Internal Validity

So does placing first year students on academic probation affect student outcomes? Instead of randomly assigning students either probation or good standing status as a randomized controlled trial, this study uses regression discontinuity design to estimate the probation impact through observed student outcomes around the probation cutoff. And one may wonder whether such estimation is able to infer that academic probation causes changes on student outcomes. Actually, as students get closer to the cutoff, they share such similar characteristics that probation estimation could be as good as randomized controlled trial. Besides, previous meta-analysis on RDD has also suggested its high internal validity to provide an accurate probation estimate within the study settings (Chaplin et al. 2018).

By applying a narrower bandwidth of 0.2 GPA, student characteristics become more balanced (Table 6). Although the t-test still shows a difference on highschool performance between treatment and comparison students (Table 3), study results in Result Section 4 has already suggested that the impact of academic probation on student dropout, Year 2 annual GPA and graduation is not “significant” under relevant models.



In fact, further restricting the bandwidth to 0.1 GPA also does not show “significant” probation impact on student outcomes.

However, as mentioned in Data Section 2.3.2, narrower GPA bandwidth will include less student samples, lowering the power of the model. With insufficient power, p-value obtained from the model is more likely to happen by chance instead of the probation cutoff rule, so its interpretation may also be in vain.

Therefore, from model results of 0.2 GPA bandwidth, in this Canadian university, there is “no evidence” to show that the academic probation policy causes:

- Increase in chances of student dropout
- Increase in second year annual GPA of remaining students
- Decrease in chances of graduation by Year 4

While there is “evidence” to show that after being placed on academic probation in the first year:

- Students whose first language are not English are less likely to dropout school
- Male students earn less second year annual GPA, and are less likely to graduate by the fourth year than female students
- Students with high highschool grades earn more annual GPA than those with low highschool grades

### 5.2.2 Campus Variation and External Validity

As the data used in this study is obtained from a large Canadian university, can the study results generalize to other universities that also have academic probation or related policies? Not likely.

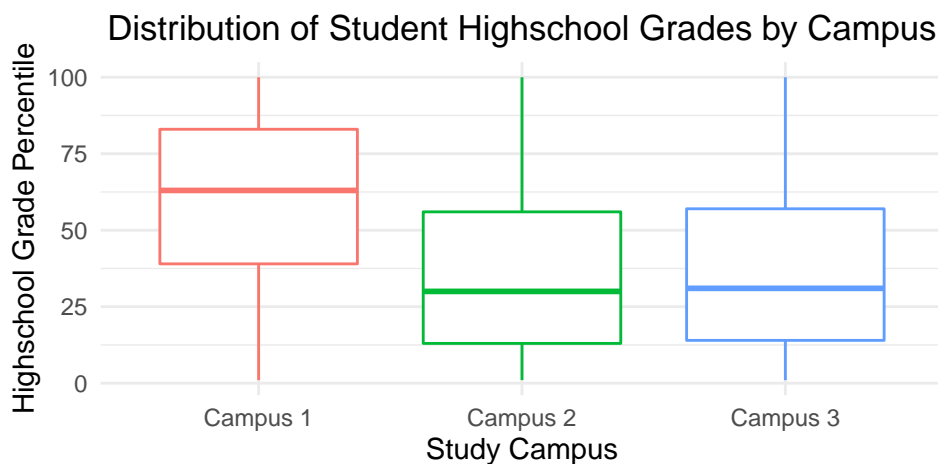


Figure 8: Distribution of Student Highschool Grades by Campus

In Institutional Background Section of Lindo’s paper, they showed a lower acceptance rate (about 55%) in Campus 1 and a higher acceptance rate (about 77%) in Campus 2 and 3. The above boxplot (Figure 8) also suggests highschool grade difference across campus. Besides, Campus 1 resembles a large US state college and Campus 2 and 3 have more part time and commuter students (Lindo, Sanders, and Oreopoulos 2010). Despite the university share same probation policy, students may still react differently towards academic probation under different campus environment. So I add a campus variable into the model constructed in Model Section 3.2.2 to examine if there are campus variations towards academic probation:

$$Y_i = \beta_0 \text{Proation}_i + f(\text{Cutoff Distance}_i) + \alpha_1 \text{Gender}_i + \alpha_2 \text{HighSchool}_i + \alpha_3 \text{Language}_i + \alpha_4 \text{Campus}_i + \epsilon_i$$

From model results of student outcomes as shown below (Table 13), students in different campus do react differently towards academic probation: Compared to students in Campus 1: (1) Students in Campus 3 are less likely to leave the university, and (2) Students in Campus 3 earn more annual GPA in the second year and are more likely to graduate by Year 4, holding other baseline characteristics constant.

As a result, campus variation towards academic probation demonstrates limited external validity of this study. Students are not likely to react similarly towards academic probation across university or college, whose demographics and general academic standards are usually different. More importantly, each university or college generally holds distinct policies towards academic probation, and it is not appropriate to use a specific probation policy in one university to infer academic probation impact on other universities solely from this study.

Table 13: Regressions for Campus Variation towards Academic Probation within 0.2 GPA bandwidth

	Logistic for Dropout	Linear for Year 2 GPA	Logistic for Graduation
Constant	0.094*** (0.000)	1.930*** (0.000)	0.358*** (0.000)
Campus 2	0.971 (0.868)	0.142*** (0.000)	1.262** (0.039)
Campus 3	0.587*** (0.003)	0.040 (0.160)	1.020 (0.852)
In Good Standing	0.707 (0.218)	-0.053 (0.263)	1.269 (0.160)
f(Cutoff Distance)	0.405 (0.466)	0.007 (0.973)	1.987 (0.352)
Gender Male	1.098 (0.518)	-0.118*** (0.000)	0.502*** (0.000)
Highschool Above Average	0.705* (0.072)	0.132*** (0.000)	1.134 (0.255)
First Language Not English	0.479*** (0.000)	-0.033 (0.210)	1.097 (0.339)
Num.Obs.	4085	3408	2899
R2		0.018	
AIC	1643.6	7192.8	3306.7
Log.Lik.	-813.816	-3587.393	-1645.342

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

<sup>1</sup> Odds Ratio in Logistic Regression. Coefficient in Linear Regression. P-value in Parentheses

## 5.3 Bias

### 5.3.1 From Data

As mentioned in the Data Section 2.2, student data in this Canadian university has already been cleaned in Lindo's study. And such cleaning will raise inevitable biases affecting the study result:

- Students with missing data for any variables of interest are cleaned. Highschool grade is the most missing variable and it is only available for students who attended highschool in the Canadian province where this university is located. These omitted students could come from other Canadian provinces as domestic students, or from other countries as international students. They generally incur a higher cost studying in this university (e.g. transportation, housing, etc.), especially international students who pay higher tuition fees than domestic students. Besides, these omitted students could come from various culture backgrounds and respond quite differently towards academic probation as suggested in this study.

- Students with academic standing not evaluated at Year 1 are cleaned. Most of these students are not evaluated due to insufficient number of attempted credits. These students may intentionally take less courses according to their academic planning, or drop some courses to prevent failing them<sup>12</sup>. No matter why these students attempt insufficient credits, their courseloads are different than those of students included in this study. Since the courseload could reflect student academic ability (Szafran 2001), students not evaluated at Year 1 may also respond differently towards academic probation.
- Students whose first entry age are not between 17 and 21 are cleaned. These students are usually older than students included in the study and may focus more on other aspects of their livings (e.g., family, work, etc.) than academics. So they may also react differently towards academic probation.

### 5.3.2 From School Policy

Even though students in this university are not likely to “play with” the probation rule itself to avoid academic probation as discussed in Model Section 3.1. There are other academic policies potentially affecting student GPA, namely “Credit/No Credit option” and “Late Withdrawal”<sup>13</sup>:

The Credit/No Credit option allows students to remove course result from their GPA but still count course credit if passing the course (at least 50% final mark, 2.0 credits maximum) before a certain deadline (usually in the middle of the semester). For example, if a student utilizes this policy on:

- A 51% grade course of 0.7 grade point. This course will count credit but not used to calculate GPA.
- A failed course less than 50% grade. This course will neither count credit nor used to calculate GPA.

The Late Withdrawal allows students to withdraw from a course before the last day of class (3.0 credits maximum). A student can use this policy when feeling behind in a course and this course will neither count credit nor used to calculate GPA.

By exploiting these policies, a student can remove courses with relative low grades. So the GPA is expected to increase **if the student knows and uses these policies**. These policies may potentially change student academic status from on probation to in good standing, violating the RDD assumption of free manipulation on forcing variable. Unfortunately, Lindo did not address these policies so that the data obtained from the original paper does not contained any information regarding these policies. It also remains obscure that to what extent first year students in this university know these policies, and whether these students will get more familiar with university policies in Year 2 to “play with” them.

## 5.4 Dirty Data

Although the original data obtained from Lindo’s paper contains detailed student information to carry on this study, I find the data dirty that could affect result accuracy through following examples:

- The original data actually records student graduation information by Year 4, Year 5 and Year 6. However, there are enormous missing values on these graduation related data (14345 missings on Year 4, 19781 missings on Year 5, 24605 missings on Year 6 out of 44362 observations). Besides, even some students are recorded to graduate by Year 4 but not recorded by Year 5 or Year 6. So I refrained to explore the probation impact on graduation by Year 5 and Year 6 because of such data inconsistency, even though Lindo did relevant analysis in their original paper.
- Some students above the probation cutoff GPA are on academic probation, and some below the probation cutoff GPA are in good standing (98 out of 44262 observations). Lindo attributed this inconsistency to administrative error in data reporting, while it remains uncertain whether there are other policies causing this inconsistency.

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<sup>12</sup>Dropping a course will not count as an attempted credit but failing a course does and the failed course will be assigned 0.0 GPA.

<sup>13</sup>This is the current academic policies of this university as of 2021. Academic polices between 1996 and 2005 might be different and could not be retrieved on the university website. While these policies may still raise potential biases of this study.

## 5.5 Enhancement

This paper proposes an adjusted 0.2 GPA bandwidth according to the university domain setting. Since this bandwidth may not be the only suitable bandwidth to examine academic probation impact, I created a interactive Shiny App that can adjust the GPA bandwidth (ranging from 0.02 GPA to 1.5 GPA) and display regression results of the model as proposed in Model Section 3.2.2. While one should keep (1) similar characteristics for RDD assumption, and (2) enough student samples for sufficient power in mind to avoid falsely interpreting the results.

This Shiny App is available at: [https://lance-hong-shi.shinyapps.io/RDD\\_academic\\_probation/](https://lance-hong-shi.shinyapps.io/RDD_academic_probation/)

## 5.6 Comment and Future Works

As a replication study, this paper does not use the exact same model as in the original paper. The original paper subsets the data into different subgroups by student gender, highschool performance and first language and uses RDD to examine the probation impact on each subgroup, while this paper includes all of those student characteristics into one model and uses RDD to examine the probation impact as a whole. Even though the analysis approach is slightly different, I believe the model used in this study is appropriate and could draw valid results.

Surely, there must be other characteristics affecting student responses towards academic probation as well (e.g., family background, financial situation, personal trait, etc.), but they are usually beyond the scope of the university administrative data recordings and are not included in the original dataset. Future researchers may consider including these student characteristics in their studies if possible.

Instead of relying on academic probation or similar policies to force students to maintain good academic standards, universities need to address underlying causes of student weak academic performances. Previous studies have investigated cognitive, emotional, behavioral and environmental factors affecting probation students (Kelley 1996), and universities should assist students recovering from learning challenges through academic success courses or programs (McGrath and Burd 2012).

## A Appendix Letter Sent to Students at Campus 2

Dear < first name >:

Your academic record indicates that you are experiencing challenges with your studies at xxxxxxxxxxxx. As a result, you have been placed “On Probation” at the end of the xxxxxxxx session. “On Probation” is an academic status applied to a student if he or she:

1. Is having difficulty achieving a term average of at least 1.7 GPA or a yearly average of 1.5 CGPA.
2. Is having difficulty meeting performance expectations and/or deadlines as outlined by the course instructor.
3. Is having difficulty achieving the minimum grades required for graduation.

A student who at the end of any session during which they are on probation has a cumulative GPA of less than 1.5 and a sessional of less than 1.7 shall be suspended. Therefore, it is imperative that you seek assistance to improve your academic standing to avoid further sanction.

Rest assured that you can improve this status and that xxxxxxxxxxxx offers assistance at many junctions. First, you can access help by making an appointment with an academic advisor in the Office of the Registrar to develop strategies to improve your academic record. Book an appointment at xxx-xxx-xxxx or online at www.xxxxxxxxxx. Second, contact xxxxxxxx for assistance with study habits, note taking, effective research, time management, study groups, and peer mentors. Finally, the xxxxxxxxxxxx offers skills and interest testing which can help you focus on your strengths.

We know that you are capable of academic success, based on your academic record at admission. A good academic record is essential for entry to Limited Enrolment programs, graduate school, and professional schools. Let us review your goals and help you develop a plan to achieve them.

You have the opportunity and available support to be successful. Please utilize our services to insure your future success.

For further information on academic status, please refer to xxxxxxxx of the Academic Calendar or here: <http://www.xxxxxxxxxxxxxx>.

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