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Ability, Gender, and Performance Standards: Evidence from Academic Probation[†]

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We use a regression discontinuity design to examine students' responses to being placed on academic probation. Consistent with a model of introducing performance standards, we find that being placed on probation at the end of the first year discourages some students from returning to school while improving the GPAs of those who do. We find heterogeneous responses across prior academic performance, gender, and native language, and discuss these results within the context of the model. We also find negative effects on graduation rates, particularly for students with the highest high school grades. (*JEL* I23, J16)

Academic probation is a nearly universal tool used by universities to ensure currently enrolled students achieve minimum academic standards. The general structure of such programs is simple—if a student's grade point average (GPA) is below a certain threshold, the student is placed on academic probation which serves as a wake-up call and can lead to escalating penalties. Our paper uses longitudinal data from three campuses at a large Canadian university to estimate the causal impact of being placed on academic probation by exploiting the discontinuous nature of the policy in a regression discontinuity (RD) design. Despite the prevalence of academic probation, we are the first to analyze its causal impacts on student outcomes.[1] More generally, our paper serves as an analysis of how individuals respond to a threat of punishment, as failure to improve one's grades after being placed on probation leads to suspension.

Due to concerns about welfare, experiments providing such a large negative incentive often are not viable. As such, examining students' responses to academic probation provides a rare opportunity to examine the impacts of a negative incentive

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[†] To comment on this article in the online discussion forum, or to view additional materials, visit the articles page at http://www.aeaweb.org/articles.php?doi=10.1257/app.2.2.95.

[1] The only prior empirical analysis of academic probation compares the mean retention rate of engineering students on probation to the mean retention rate of those in good academic standing (Alejandro Scalise et al. 2000).

in an important real-world setting. While there is a fairly extensive literature on the causal effects of other explicit university policies, these studies have focused primarily on positive incentives and services.[2] A handful of recent papers examining the effects of college remediation stand out as the only prior studies of negative incentives in a postsecondary setting.[3] Like students placed on academic probation, students placed into remedial classes are given a signal that their performance is not satisfactory. Thus, studies that measure the effect of being placed into remedial classes capture the combined impact of the negative signal and the impact of being required to take remedial classes. Similarly, in this paper, we measure the combined effect of the negative signal and the effect of being subjected to a more rigid performance standard in the next term.

Specifically, once a student has been placed on academic probation, she must earn a GPA above the campus-set standard in the next term or she will be suspended from the university for one year. Placing students on academic probation is equivalent to setting a minimum standard for their future performance. In this sense, our results have implications for the wide variety of circumstances in which setting a standard might be used as a means of affecting performance. In addition to school administration, applications include management, parenting, and health and safety regulation.

While we are the first to consider the effect of a performance standard at the university level, a large prior literature has examined performance standards at the secondary level in the form of high school exit exams. One of the issues this literature has tried to address is whether or not high school exit exams discourage students from remaining in school, as this concern has been a focal point for critics of the increasingly popular policy. Empirical studies have found mixed results in this regard.[4]

Our results also provide an opportunity to empirically examine theoretical models of imposing performance standards. Roland Bénabou and Jean Tirole (2000) outline one such model which predicts that setting a performance standard involves an inherent trade-off between motivating some agents to improve their performance and discouraging other agents from making any attempt at all. We explore the extent of this trade-off by analyzing the effect of being placed on academic probation on

[2] Examples include papers analyzing the effects of advising and merit scholarships (Joshua Angrist, Daniel Lang, and Philip Oreopoulos 2009; Edwin Leuven, Hessel Oosterbeek, and Bas van der Klaauw forthcoming), tuition costs (Iida Häkkinen and Roope Uusitalo 2003; Martin Heineck, Mathias Kifmann, and Norman Lorenz 2006; Pietro Garibaldi et al. 2007), financial aid (Stephen L. DesJardins, Dennis A. Ahlburg, and Brian P. McCall 2002), and appointment to the Dean's List (W. Burleigh Seaver and Richard J. Quarton 1976; revisited by Thomas D. Cook and Donald T. Campbell 1979).

[3] See Brian A. Jacob and Lars Lefgren (2004), Francisco Martorell and Isaac McFarlin (2007), Juan Carlos Calcagno and Bridget Terry Long (2008), and Eric P. Bettinger and Long (2009), among others.

[4] There are two distinct types of studies in this literature: studies of the effects of the presence of high school exit exams and studies of the effects of failing high school exit exams. Both strands of literature have produced mixed results. In the former, Chandra Muller (1998), Muller and Kathryn S. Schiller (2000), Martin Carnoy and Susanna Loeb (2003), and John Robert Warren and Krista N. Jenkins (2004) find that exit exams have no effect on dropout rates while Audrey. L. Amrein and David C. Berliner (2003) find that they increase dropout rates. Jacob (2001) and Thomas S. Dee and Jacob (forthcoming) show that there is substantial heterogeneity in students responses. In the latter, Bryan W. Griffin and Mark H. Heidorn (1996); Dewey G. Cornell, Jon A. Krosnick, and LinChiat Chang (2006); John P. Papay, Richard J. Murnane, and John B. Willett (2008); and Dongshu Ou (2009) all find evidence that failing exams cause at least some groups of students to drop out of school early while Martorell (2004) finds no evidence of this type of response.

the decision of students to drop out and on the subsequent performance for those who remain.

This paper also contributes to the growing literature on gender differences in response to educational incentives. Previous studies have found that women are more responsive to positive incentives than men. Women respond to advising and scholarship programs while men do not (Angrist, Lang, and Oreopoulos 2007); tuition reductions impact college completion rates for women more than men (Susan Dynarski 2008); and the effects of high school achievement awards appear limited to women (Angrist and Victor Lavy 2002). However, because the existing literature has focused on policies providing positive incentives, little is known about gender differences in response to negative incentives.

Our RD research design is motivated by the idea that students with a GPA just above the academic probation threshold after the first year provide a good counterfactual for those who have a GPA just below the academic probation threshold. As long as characteristics related to student outcomes are continuous through the threshold, we can measure the effect of being placed on probation in a RD design framework. It is important to keep in mind that, like the students placed on probation, "control" students must also get bad grades in their first year to fall near the cutoff. Poor academic performance in the first year of college is likely to have an effect on behavior regardless of whether or not a student is placed on probation. As such, effects that we estimate are over and above the effects of getting bad grades alone. We can think of our estimates as identifying the effect of being sent a letter that explicitly states a student has performed poorly and informs them that they are being subjected to the performance standard described above.

Our results indicate that the effects of academic probation are remarkably heterogeneous. Consistent with Bénabou and Tirole's (2000) model, being placed on academic probation after the first year discourages some students from returning to school and motivates those who remain to improve their subsequent performance. We find differences across prior academic performance, gender, and native language. We find that being placed on academic probation doubles the probability of dropping out for students with high school grades above the median, but has little impact on students with high school grades below the median. Being placed on probation doubles the probability that men drop out, but has no effect on the decision of women to drop out. Finally, probation increases the probability that native English speakers drop out, and has no effect on the decision of nonnative English speakers to drop out. Further, we find that being placed on probation improves the grades of returning students across all groups, and we show that these effects are too large to be attributed to nonrandom attrition.

Finally, we consider the effect of being placed on academic probation on graduation rates. We find being placed on probation simultaneously motivates some students to improve their grades while causing others to drop out, so there is no clear prediction of a positive or negative effect on the probability of graduation. Overall, our estimates suggest that being placed on academic probation reduces graduation rates, especially for students who performed better in high school.

The rest of the paper is organized as follows. Section I describes the university and its academic probation program in more detail. Section II reviews Bénabou and

Tirole's (2000) model of performance standards. Sections III and IV describe the data and our empirical strategy. Section V presents our main results. Section VI discusses our main results. Section VII concludes.

I. Institutional Background

Our data comes from a large Canadian university made up of three individual campuses: one central campus and two smaller satellite campuses. The central campus (Campus 1) has an acceptance rate of about 55 percent, while the two satellite campuses (Campus 2 and Campus 3) have acceptance rates of approximately 77 percent. The central campus resembles a large US state college, while the satellite campuses have more part-time and commuter students. Campus 1 and Campus 2 share identical rules regarding academic probation—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. For the purposes of our analysis, students from all three campuses have been combined into a single sample.[5] We account for the difference in cutoff points in our RD analysis by using students' distances from their campus' cutoff as the running variable rather than absolute GPA.[6]

When a student is placed on academic probation, a letter is sent notifying them of their current academic standing. The letter specifies why the student has been placed on probation, how to regain good academic standing, and the consequences of failing to improve. The letter also encourages students to continue at the university and improve their academic performance, and lists various services provided by the university aimed at helping them to do so. A copy of the letter sent to students at Campus 2 is in the Appendix.

Because many freshman classes span the entire year, students' academic standings are not evaluated for the first time until the end of their first year.[7] At Campus 1 and Campus 2, students' academic standings are evaluated again at the end of every subsequent full scholastic year and summer term. At Campus 3, students' academic standings are evaluated again at the end of each subsequent term.

Students on academic probation face the threat of suspension after subsequent sessions if their grades do not improve. At all campuses, students on probation can avoid suspension and return to good academic standing by bringing their cumulative GPA up to the cutoff.[8] Students who fail to sufficiently improve their grades are

[5] In an earlier version of the paper, we used this across-campus variation to examine the effects of academic probation in a difference-in-difference framework. These results were similar to the RD estimates but imprecise due to a smaller sample size.

[6] One might expect academic probation to have heterogeneous impacts across campuses since the rules and composition of students are somewhat different across the campuses. However, in results not shown, we find that the effects of being placed on probation are fairly similar across the three campuses.

[7] Students also must attempt a minimum number of credits before they are evaluated. We omit all students who have not yet been evaluated by the end of their first full year. It is possible this is endogenous, though unlikely. If a student drops a course before the deadline, the course grade will not be counted in determining academic probation (or GPA in general). If this incentive to drop is continuous through the cutoff, however, this should not pose a problem.

[8] Students who do not raise their cumulative GPA up to the cutoff can still avoid suspension by achieving a per-session GPA above a particular minimum specified by their campus. However, this will not be relevant for students close to the cutoff, as it will be weakly easier to achieve the cumulative GPA requirement.

suspended for one full academic year. If suspended students choose to 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.

II. Theoretical Background

In this section, we first review Bénabou and Tirole's (2000) model of agents' responses to a performance standard. The model is framed as a game between a principal and an agent, where the principal has the ability to set standards for the agent. While Bénabou and Tirole (2000) consider the model from the perspective of both the agent and the principal, we focus only on the agent. We then relate this model to academic probation.

Consider an agent facing a choice between three possible paths: option 1, option 2, or neither. If the agent chooses neither option, both her costs and benefits are zero. If the agent attempts option i, she incurs cost c_i and, if successful, gains the benefit V_i. If the agent attempts option i and fails, she still incurs a cost but receives no benefit. Option 1 is an easy option with a low potential benefit while option 2 is a difficult option with a high potential benefit. Costs and benefits can be summarized as

$$(1) \qquad 0 < c_1 < c_2 \qquad 0 < V_1 < V_2 .$$

Ability is expressed as the probability of successfully completing either option, where higher ability translates into a higher probability of success. The probability of success for either option is θ. Assuming the agent has perfect information regarding her ability (θ), she solves

$$(2) \qquad \max\{0, \theta V_1 - c_1, \theta V_2 - c_2\}.$$

Let $\underline{\theta}$ be the level of ability for which the agent is indifferent between attempting neither option and attempting option 1, and let $\overline{\theta}$ be the level of ability for which the agent is indifferent between attempting option 1 and attempting option 2. With the following assumption,

$$(3) \qquad \underline{\theta} \equiv \frac{c_1}{V_1} < \overline{\theta} \equiv \frac{c_2 - c_1}{V_2 - V_1} < 1,$$

which ensures that both options are optimal for at least some θ. It can be shown that the lowest ability individuals ($\theta < \underline{\theta}$) choose neither option, the highest ability individuals ($\overline{\theta} < \theta$) choose the difficult option, and the remaining individuals ($\underline{\theta} < \theta < \overline{\theta}$) choose the easier option.[9]

[9] Interestingly, the same results arise from a model in which the agent is sure to be successful in whichever task she chooses, but the cost of each task is inversely related to the ability measure θ. That is, the agent would solve $\max\{0, V_1 - (c_1/\theta), V_2 - (c_2/\theta)\}$. Expressed in this way, the model can feature decreasing marginal returns to ability. The same results can also arise from a model in which the probability of success is increasing in ability and the cost is decreasing in ability. For example, if the agent solves $\max\{0, \sqrt{\theta}V_1 - (c_1/\sqrt{\theta}), \sqrt{\theta}V_2 - (c_2/\sqrt{\theta})\}$.

If the principal removes option 1 as a possible course of action, perhaps by forbidding it or imposing an additional cost on it, such that it is always inferior to other options, then the agent will choose option 2 if and only if

$$\theta \geq \frac{c_2}{V_2} \equiv \theta^* \tag{4}$$

and pursue neither option otherwise. Within the range of agents who would choose option 1 if it remained a possibility, the model predicts those with the higher ability will work harder (engaging in option 2), while those with the lower ability will give up (pursuing neither option).[10]

This model naturally lends itself to analyzing how students might respond to being placed on academic probation. Consider the choice faced by two students (agents) whose first year GPAs were near the academic probation threshold, one just above and one just below. Since the student just above the threshold remains in good academic standing, his options are unrestricted. These options can be placed into three categories: return to school with the intent of achieving some low GPA (option 1), return with the intent of achieving some high GPA (option 2), or drop out of school (neither option 1 nor 2).

As a result of being placed on probation, the student just below the cutoff faces a different set of choices. We can think of academic probation as the administration forbidding, or placing an extremely large negative incentive on, pursuing option 1. In the framework of the model, if the student below the cutoff chooses to pursue option 1, she will be suspended from the university.

The testable implications of the model's theoretical framework are the following:

- Forbidding option 1 will increase the overall probability of students dropping out.
- Forbidding option 1 will increase the performance of those who return.
- Forbidding option 1 will cause relatively low-ability students to drop out and relatively high-ability students to return and work harder.[11]

III. Data

The data used in the analysis are from an administrative dataset of college students from the large Canadian university described in Section I. Observations are at the student level and cover a nine-year period from 1996 to 2005 with each scholastic year broken into fall, winter, and summer terms. The data includes student term registration status, GPA, academic standing, gender, age, first language, and a measure of high school performance. We use the set of background variables for falsification tests and as controls in some regression specifications.

We restrict the sample to students we can potentially observe for two years. Since the data are through the end of the 2005 school year, we restrict to students who

[10] Specifically, those with θ in $[\theta^*, \overline{\theta}]$ will now choose option 2, while those with θ in $[\underline{\theta}, \theta^*]$ will now choose not to pursue either option.

[11] Robert M. Costrell (1994) discusses educational performance standards in a different theoretical framework that leads to similar predictions.

entered in the 2004 school year or earlier. This leaves eight cohorts of students. We omit students with missing data for any variables of interest. The variable that is most often missing is the high school grade measure which is only available for students who attended high school in the province (84 percent of the sample). This variable is a student's average GPA in courses that are universally taken by high school students in the province. This measure of high school achievement is intended to be consistent across high schools and is used as a part of the criteria that determines admissions at Canadian universities.

We also restrict the sample to students entering the university between the ages of 17 and 21 (99 percent of the remaining sample). Additionally, we keep only students who have had their academic standing evaluated at the end of their first year (98 percent of the remaining sample).[12] Finally, we limit the sample to students within 1.2 grade points of their academic probation cutoff (corresponding to the largest bandwidth we consider in our regressions). This effectively drops students who failed all of their first year classes in addition to students who cleared the cutoff by a wide margin. The resulting sample includes 25,389 students. Further restricting the sample to students within 0.6 of the cutoff leaves 12,530 students.

The first column of Table 1 shows the descriptive statistics for the restricted sample. The students average entry age is 18.7 years. Approximately 38 percent are male, 72 percent have English as their first language, and 87 percent were born in North America.[13] Fifty-one percent of the students attend Campus 1 (the central campus). Of the remaining students, 20 percent attend Campus 2 and 29 percent attend Campus 3. For the most part the means *at the limits of the cutoff* are most relevant, and these are discussed in subsequent sections. Before proceeding, we should note that a sizable fraction of students in our sample (25 percent) are placed on academic probation after their first year.[14] While it is unfortunate that so many students fail to meet their campus' academic requirements, this is a positive aspect for our research design because it improves our ability to obtain estimates on both sides of the probationary cutoff.

IV. Empirical Strategy

We begin by estimating the impacts of being placed on academic probation after the first year. At the end of the first year the probation status for student i at campus c is a deterministic function of their GPA, which can be expressed as

$$PROB_{ic}^{year\,1} = 1(GPANORM_{ic}^{year\,1} < 0), \tag{5}$$

where $GPANORM_{ic}^{year\,1}$ is the distance between student i's first year GPA and the probationary cutoff at her campus c. Because the discontinuity in probation status is "sharp," as we will show in Section VA, as long as other student characteristics

[12] In almost all cases, if a student was not evaluated it was due to an insufficient number of attempted credits.

[13] If a student's first language is not English, it is usually an Asian language. Despite being a Canadian institution, less than 1 percent of students have French as their first language.

[14] Of the entire student body, 16 percent are placed on probation after their first year.

Table 1—Summary Statistics

	Mean	SD
Characteristics		
High school grade percentile	33.33	23.29
Credits attempted in first year	4.43	0.53
Age at entry	18.72	0.74
Male	0.38	0.48
English is first language	0.72	0.45
Born in North America	0.87	0.34
At Campus 1	0.49	0.50
At Campus 2	0.21	0.41
At Campus 3	0.31	0.46
Outcomes		
Distance from cutoff in 1st year	0.11	0.33
On probation after 1st year	0.35	0.47
Ever on academic probation	0.46	0.50
Left university after 1st evaluation	0.05	0.22
Distance from cutoff at next evaluation	0.47	0.81
Ever suspended	0.16	0.37
Graduated by year 4	0.29	0.45
Graduated by year 5	0.56	0.50
Graduated by year 6	0.67	0.48

Notes: For all variables except graduation rates and next evaluation distance from the cutoff, the sample consists of the 12,530 students within 0.6 grade points of the cutoff in their first year. Graduation rate samples are 8,821 for four years, 7,293 for five years, and 6,005 for six-years. 11,258 students are observed with a GPA following their first evaluation.

related to the outcomes are continuous through the threshold, the treatment effect for students near the threshold can be obtained by comparing the outcomes of students just below the threshold to those just above the threshold.

The following equation can be used to estimate the effects of academic probation on subsequent student outcomes:

$$Y_{ic} = m(GPANORM_{ic}^{year1}) + \delta 1(GPANORM_{ic}^{year1} < 0) + u_{ic}, \tag{6}$$

where Y_{ic} is an outcome for student i at campus c, $m(GPANORM_{ic}^{year1})$ is a continuous function of students' standardized first year GPAs (the distance from their campus' probationary cutoff), $1(GPANORM_{ic}^{year1} < 0)$ is an indicator equal to one if the student's GPA is below the probationary cutoff, and u_{ic} is a random error term. The coefficient of interest is δ, the estimated impact of being placed on academic probation after the first year.

As suggested by Guido W. Imbens and Thomas Lemieux (2008), we estimate the discontinuity using local linear regressions with rectangular kernel weights.[15] We present results using a bandwidth of 0.6 grade points. In prior versions of the paper (available upon request), we have shown similar results using bandwidths of 0.3 and 1.2 grade points, results controlling for observables, and results based on models

[15] Our regression equation is given by:

$$Y_{ic} = \alpha + \delta 1(GPANORM_{ic}^{year1} < 0) + \beta(GPANORM_{ic}^{year1}) + \gamma(GPANORM_{ic}^{year1}) \times 1(GPANORM_{ic}^{year1} < 0) + u_{ic},$$

where the notation is the same as in equation (6).

controlling for a polynomial in the running variable. Since GPA data are discrete (in hundredths of a grade point), we cluster the standard errors as recommended by Davis S. Lee and David Card (2008).

V. Results

In this section, we begin by testing the validity of the regression discontinuity design. Then, we examine the effects of being placed on academic probation on the decision of students to drop out, subsequent GPAs, probabilities of suspension, and graduation rates in addition to the heterogeneity of these effects across students' prior academic performance, gender, and native language.

A. *Tests of the Validity of the RD Approach*

Nonrandom sorting is a main concern with any RD design in which those who could be affected by the policy might know the cutoff. In our case, this would appear if students just below the cutoff were actively influencing their GPAs to avoid probation (e.g., convincing teachers to give them a higher grade to raise their GPA above the cutoff point) or expending just enough effort to get grades above the cutoff. By focusing on academic probation status at the end of the first year, we decrease the likelihood of this concern. First year students are less familiar with campus policies and, thus, less likely to know what grades would be required to avoid academic probation.[16] In addition, though Campus 3 has semester-length first-year courses, most first year courses span the entire year at Campuses 1 and 2, and the majority of the grade is based on evaluation at the end of the term. This makes it difficult for students to correctly "hit" a performance point just above the cutoff, especially given that their overall GPA is calculated over several courses.

If sorting were a problem, we would expect to see a discontinuity in the distribution of grades at the cutoff, as a disproportionate number of students would fall just above the cutoff relative to the number of students just below the cutoff.[17] Figure 1 shows the distribution of students' first year grades relative to their campus cutoff, with cell sizes of 0.1 grade points. Using each of these cells as an observation, the figure also shows the predicted cell sizes based on local linear regressions using rectangular kernel weights and a bandwidth of 0.6. The estimated discontinuity at the threshold is not statistically significant, indicating that the distribution of students is continuous through the threshold.[18] We have also verified that the discontinuity is not significant using smaller cell sizes and bandwidths.[19]

[16] To verify that those most likely to be affected by probation were no more likely to be informed about the policy, we conducted a survey in an introductory economic course regarding the policies of academic probation. Only 15 percent of students said they knew the academic probation cutoff "for sure." An additional 19 percent said they were "pretty sure" they knew the cutoff. We found no evidence that students' grades are related to their knowledge about academic probation.

[17] At the same time, this might not be the case if the distribution of grades is fixed. For example, there might be a situation in which some students manipulate their grades to get themselves above the cutoff but, as a result of their efforts, other marginal students are pushed below the cutoff.

[18] This test is similar to that proposed by Justin McCrary (2008).

[19] We have also verified that there are not significant discontinuities in the distributions of students in each of the subgroups we consider in our analysis.

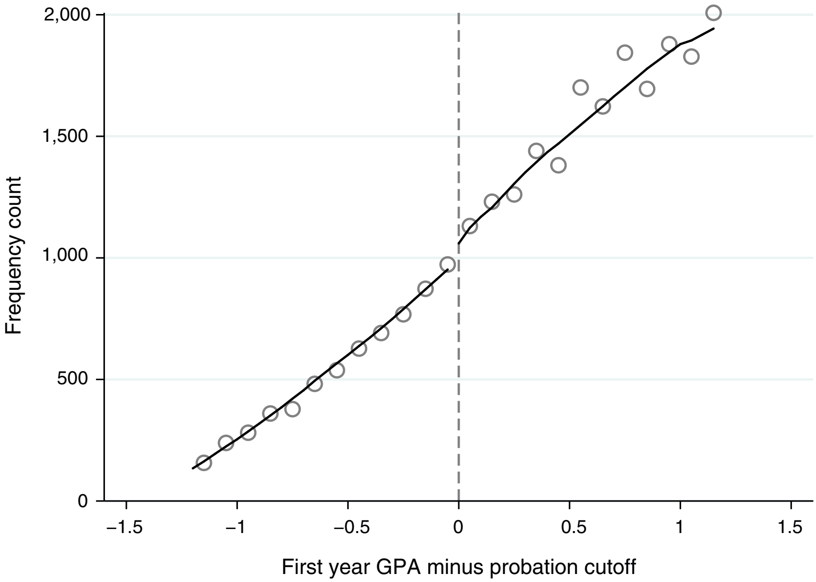

Figure 1. Distribution of Student Grades Relative to their Cutoff

Notes: Each small hollow circle indicates the number of students with a distance from their cutoff within 0.05 points (including the lower, but not the upper, endpoint). Using each of these cells as an observation, the curve is predicted from local linear regressions with a bandwidth of 0.6 using rectangular kernel weights. The estimated control mean is 1059 and the estimated discontinuity is 58 (p-value $= 0.219$).

Our research design requires both observable and unobservable characteristics related to student outcomes to be continuous through the threshold. Table 2 explores the extent to which a wide range of observable characteristics are continuous through the cutoff. Significant discontinuities would indicate that students with particular characteristics are more or less able to manipulate their grades so as to avoid being placed on probation. As a whole, these estimates support the validity of our research design. We find no significant discontinuities in students' high school grades, credits attempted in the first year at the university, age at entry, gender, birthplace, native language, or campus attended.

B. *First Year GPAs and Academic Probation*

Figure 2 and the first panel of Table 3 show the estimated discontinuity in probation status at the end of the first year. Because this discontinuity is sharp, discontinuities in other student outcomes can be interpreted as the causal effect of being placed on probation at the end of the first year.[20]

The second panel of Table 3 shows the estimated impact on the probability that a student is *ever* placed on academic probation. These estimates make it clear that a

[20] While the estimated discontinuity is approximately equal to one, it may not be *identically* equal to one because of administrative errors in data reporting.

Table 2—Estimated Discontinuities in Observable Characteristics

	HS grade percentile ranking (1)	Credits attempted in 1st year (2)	Male (3)	Age at entry (4)	Born in North America (5)	English is 1st language (6)	Attending campus 1 (7)	Attending campus 2 (8)
First year GPA < cutoff	0.450	0.024	0.015	0.000	0.017	−0.037	0.012	−0.010
	(1.259)	(0.076)	(0.032)	(0.024)	(0.013)	(0.024)	(0.034)	(0.027)
Constant (control mean)	30.991***	4.386***	18.719***	0.374***	0.864***	0.729***	0.444***	0.217***
	(0.745)	(0.046)	(0.021)	(0.012)	(0.008)	(0.015)	(0.022)	(0.018)
Observations	12,530	12,530	12,530	12,530	12,530	12,530	12,530	12,530

Notes: Estimated standard errors, clustered on GPA, are displayed in parentheses. Estimates are based on linear regression as described in Section IV, with rectangular kernel weights and a bandwidth of 0.6.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

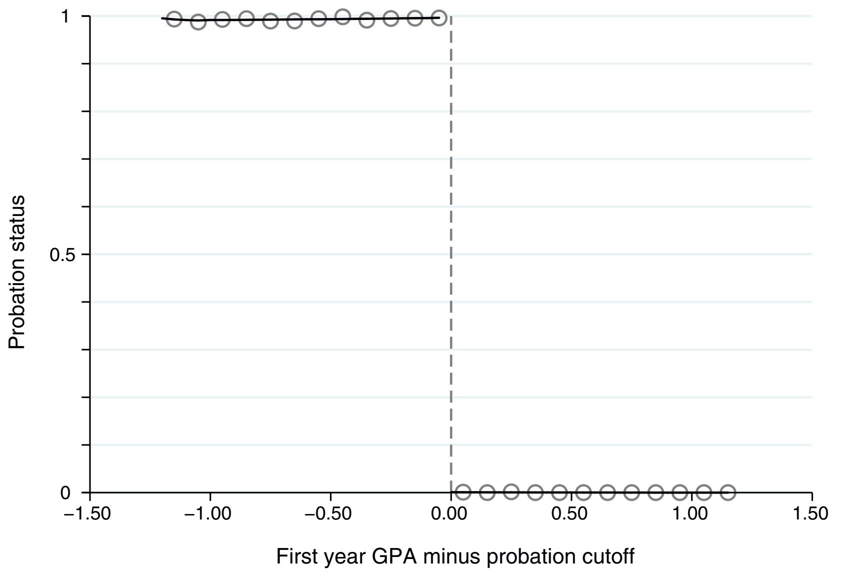

Figure 2. Probation Status at the End of the First Year

Notes: Each hollow circle is the mean of the outcome in an interval of 0.05 around the point (including the lower, but not the upper, endpoint). The curve is predicted from local linear regressions with a bandwidth of 0.6 using rectangular kernel weights.

sizable fraction of students who just pass the threshold at the end of their first year fall below the threshold in later terms and are subsequently placed on academic probation. While there are some differences across groups, this occurs for 33 percent of such students on average. It is important to keep this in mind when interpreting the results of our analysis. The effects that we estimate measure the impact of being placed on academic probation at the end of the first year of college in a setting in which "safe" students face the real possibility of being placed on probation in future terms. In other words, the controls might be thought of as receiving a much weaker form of the same treatment, and the effects that we estimate are over and above the effect of such a treatment.

Table 3—Estimated Discontinuity in Probation Status

Relevant group	All (1)	HS grades < median (2)	HS grades > median (3)	Male (4)	Female (5)	Native English (6)	Nonnative English (7)
Dependent variable: On academic probation after first evaluation							
First year GPA < cutoff	0.994***	0.995***	0.990***	0.990***	0.996***	0.993***	0.997***
	(0.002)	(0.002)	(0.006)	(0.005)	(0.002)	(0.002)	(0.003)
Constant (control mean)	0.001	0.001	0.001	0.001	0.001	0.001	0.000***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	12,530	9,473	3,057	4,701	7,829	9,006	3,524
Dependent variable: Ever on academic probation							
First year GPA < cutoff	0.665***	0.653***	0.705***	0.625***	0.690***	0.677***	0.635***
	(0.014)	(0.014)	(0.023)	(0.016)	(0.017)	(0.016)	(0.023)
Constant (control mean)	0.330***	0.343***	0.286***	0.366***	0.308***	0.317***	0.362***
	(0.014)	(0.014)	(0.022)	(0.015)	(0.017)	(0.016)	(0.022)
Observations	12,530	9,473	3,057	4,701	7,829	9,006	3,524

Notes: Estimated standard errors, clustered on GPA, are displayed in parentheses. Estimates are based on linear regression as described in Section IV, with rectangular kernel weights and a bandwidth of 0.6.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

C. *The Immediate Response to Academic Probation*

The immediate question that all students face at the end of their first year is whether or not to continue at the university.[21] Students who have been placed on academic probation have been informed that they will be suspended if their GPAs do not meet the campus-set standard in their next term.[22] However, their continued enrollment is not impeded in any other way at that point in time.

The first column of Table 4 shows the estimated impact on the decision of students to permanently leave the university at the end of their first year. The estimate, which is statistically significant at the 5 percent level, indicates that being placed on academic probation at the end of the first year increases the probability that a student leaves the university by 1.8 percentage points, or by 44 percent of the control mean.[23]

Figure 3 and columns 2–7 of Table 4 explore the extent to which different subgroups of students respond in different ways to being placed on probation at the end of the first year.[24] These results suggest that the average effect masks substantial heterogeneity.

[21] Charles F. Manski (1989) and Joseph G. Altonji (1993) develop extensive models that explore the sequential nature of the schooling decision under uncertainty.

[22] In results not shown, we find that suspension is a credible threat. Being placed on probation substantially increases the probability that students are ever suspended.

[23] It should be noted that the control mean is not the overall dropout rate but, rather, the drop-out rate for students just above the cutoff.

[24] In results not shown, we examined the response to being placed on probation in years beyond the first year. In order to maintain a proper control group, this analysis requires dropping any students placed on probation in any earlier year. This restriction, in addition to attrition, leads to substantially smaller sample sizes and no results were statistically significant.

Table 4—Estimated Effect on the Decision to Leave after the First Evaluation

Relevant group	All (1)	HS grades < median (2)	HS grades > median (3)	Male (4)	Female (5)	Native English (6)	Nonnative English (7)
First year GPA < cutoff	0.018**	0.013	0.032*	0.037**	0.006	0.028***	−0.004
	(0.007)	(0.008)	(0.017)	(0.015)	(0.009)	(0.010)	(0.011)
Constant (control mean)	0.041***	0.045***	0.026***	0.038***	0.043***	0.047***	0.025***
	(0.004)	(0.005)	(0.007)	(0.007)	(0.004)	(0.005)	(0.007)
Observations	12,530	9,473	3,057	4,701	7,829	9,006	3,524

Notes: Estimated standard errors, clustered on GPA, are displayed in parentheses. Estimates are based on linear regression as described in Section IV, with rectangular kernel weights and a bandwidth of 0.6.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

The estimated impact on students with high school grades below the median of those entering the university is small in magnitude and not significant. Our results suggest that the discouragement effect is greater for students that performed relatively better in high school (above the median of students entering the university). For these students, we find that being placed on probation at the end of the first year more than doubles the probability of dropping out immediately (significant at the 10 percent level). The estimated impact is so great for this group of students that they are just as likely to drop out as their counterparts who earned lower grades in high school.

We also find heterogeneous effects across gender. Our estimates indicate that being placed on academic probation doubles the probability that men drop out at the end of their first year, but has no effect on the decision of women to continue at the university. In results not shown, we find this gender difference does not appear to be driven by differences in the types of courses that men and women attempt in their first year.[25] The results that follow indicate that it is not that women do not respond to being placed on probation, but that they respond differently.[26]

Last, we find that probation increases the probability of dropping out for native English speakers, but that there is no impact on nonnative English speakers. It is important to note that this difference cannot be attributed to characteristics specific to students who move to Canada for college since all of the students in the sample attended high school in the same province.[27]

[25] Specifically, we have separately considered the impact for students who took first year courses that disproportionately enrolled men and for students who took first year courses that disproportionately enrolled women. Regardless of the gender composition of the peers in their first year courses, we find no evidence that being placed on academic probation impacts the decision to drop out for women. We do find evidence that it impacts men, however. We have also analyzed the impact for students who took at least half of their first year credits in science courses versus those who did not. Similar gender differences appear in these results.

[26] In results not shown, we have separately estimated the effects for men with high school grades above the median, women with high school grades above the median, men with high school grades below the median, and women with high school grades below the median. While the estimates are imprecise, they indicate that the discouragement effect is greater for students with high school grades above the median regardless of gender. Similarly, the discouragement effect is greater for men than women regardless of which group, based on high school grades, is considered. It should not be surprising, then, that the discouragement effect is greatest for men with higher high school performance. For these students, being placed on probation increases the probability of dropping out by 6.6 percentage points.

[27] Those who attended high school outside the province were omitted due to a missing high school grade measure.

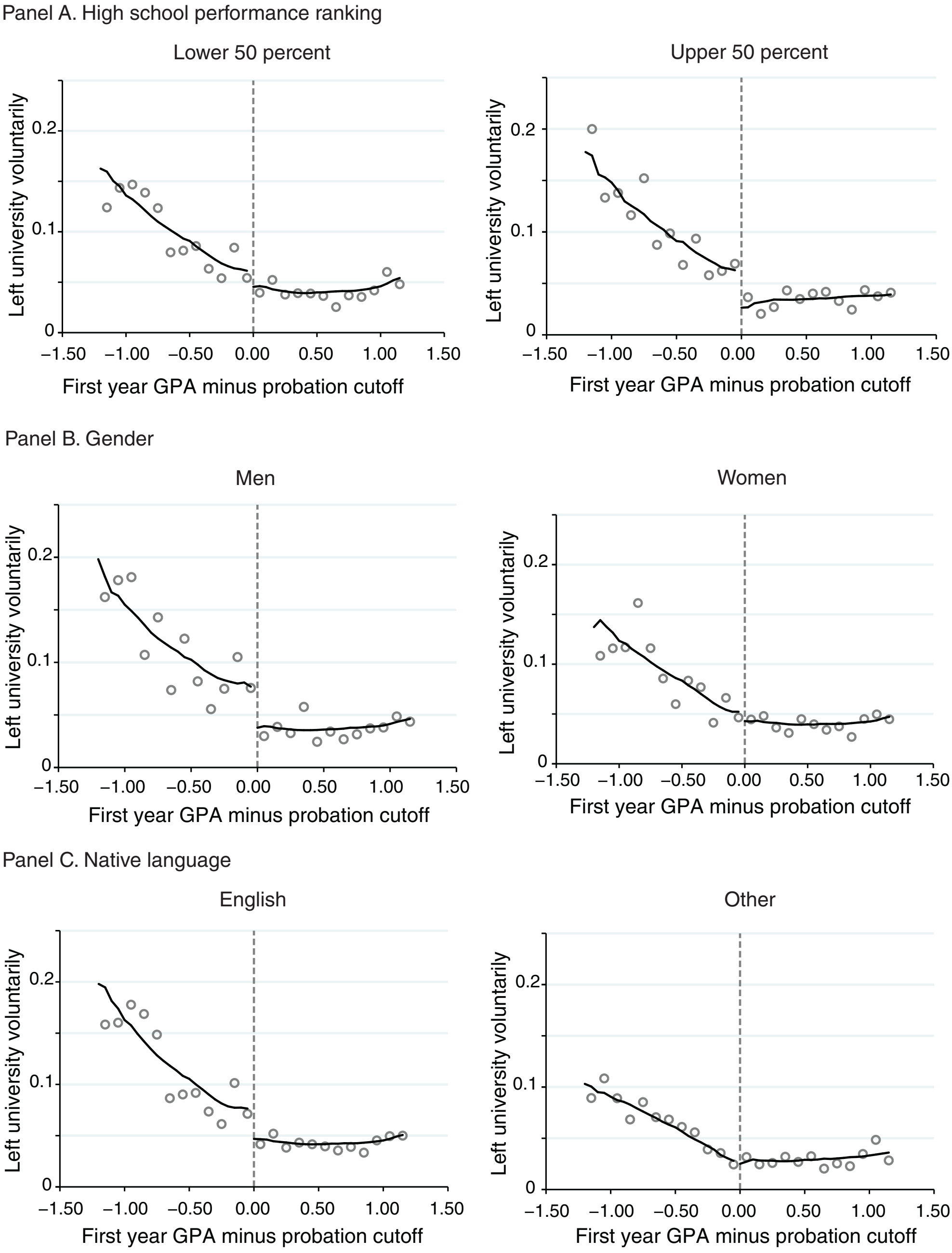

FIGURE 3. STRATIFIED RESULTS FOR VOLUNTARILY LEAVING SCHOOL AT THE END OF THE FIRST YEAR

Notes: Each hollow circle is the mean of the outcome in an interval of 0.05 around the point (including the lower, but not the upper, endpoint). The curve is predicted from local linear regressions with a bandwidth of 0.6 using rectangular kernel weights.

D. *The Impact on Subsequent Performance*

Students on academic probation who choose to remain at the university have a substantial incentive to improve their grades to the campus-set standard. Failing to do so results in being suspended from the university for a year. Figure 4 and the first column of Table 5 show the impact of being placed on academic probation on the subsequent GPAs of students using the full sample. Specifically, the outcome variable is a student's GPA in the next session in which they are evaluated.[28] The estimates suggest that being placed on academic probation causes students to improve their GPAs by approximately 0.23 grade points, a 74 percent greater improvement than students who just surpass the probationary cutoff. Columns 2–7 show that the estimated effects on GPAs are also positive when we separately consider groups defined by students' prior academic performance, gender, and native language.

It is important to note that these estimates might be biased by the effect of academic probation on the composition of students who continue to enroll in the university. For example, if academic probation results in the attrition of relatively low-ability students within any group under consideration, then we would expect the estimated impact on GPAs to be positive, even if being placed on probation has no effect on individual behavior beyond the choice to drop out. On the other hand, if the highest ability students are most discouraged from returning to the university, then the estimated impact on GPAs will be biased downward.

Table 5 also presents results from a formal bound analysis using the trimming procedure suggested by Lee (2008), with bootstrapped standard errors in parentheses. The intuition behind this analysis is straightforward. To find a lower bound for the estimated impact on students' GPAs, we assume that being placed on academic probation causes students to drop out who would have performed worst in the subsequent term if they had remained. Thus, we can make the control group comparable by dropping the bottom students from its distribution. The estimated impact on the probability of dropping out at the end of the first year provides the share of students who need to be dropped to make the groups comparable.[29] A similar procedure, trimming the top students from the control group's distribution, is used to estimate the upper bound.[30] This bound analysis demonstrates that, for all of the samples we consider, the positive effects we find on students' subsequent GPAs are too great to

[28] Note that the "next session" will be a summer session if students are enrolled in summer classes and a second year session if they are not. If we were to use only second year GPAs, there would be missing data for students placed on academic probation after their first year who do poorly in summer school and are suspended for their second year. While summer school grades tend to be higher than grades during the rest of the year, in results not shown but available upon request, we find no statistically significant impact of academic probation on the probability that a student takes summer courses, and estimates are nearly identical when controlling for whether or not a student's next session is in the summer.

[29] Note that in any bootstrap replications in which the estimated effect on dropping out is negative, students from the top of the treatment group's distribution need to be dropped to make the treatment and control groups comparable.

[30] The distribution of controls referred to here are those students in good academic standing who are given a non-zero weight in the analysis (those within the 0.6 bandwidth). We should note that this procedure was developed for standard regression equations and does not apply directly to regression discontinuity designs, but remains useful as an illustration of how large the biases could be. The optimal trimming strategy for regression discontinuity designs would likely entail more trimming near the cutoff. Although we have not done this per se, we have verified that our results, including the bound estimates, are robust to using smaller bandwidths.

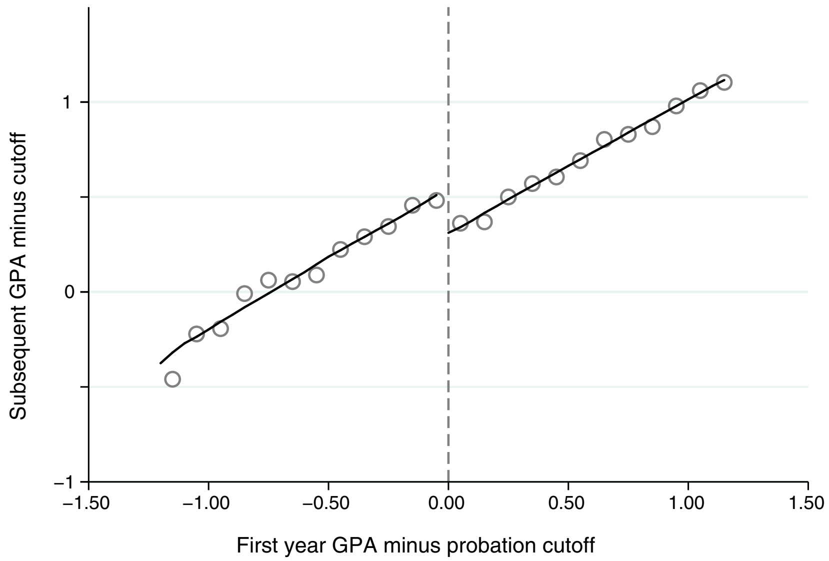

FIGURE 4. GPA IN NEXT ENROLLED TERM

Notes: Each hollow circle is the mean of the outcome in an interval of 0.05 around the point (including the lower, but not the upper, endpoint). The curve is predicted from local linear regressions with a bandwidth of 0.6 using rectangular kernel weights.

TABLE 5—ESTIMATED DISCONTINUITIES IN SUBSEQUENT GPA

Relevant group	All (1)	HS grades < median (2)	HS grades > median (3)	Male (4)	Female (5)	Native English (6)	Nonnative English (7)
Panel A. Dependent variable: Next term GPA							
First year GPA < cutoff	0.233***	0.247***	0.179**	0.207***	0.246***	0.229***	0.240***
	(0.026)	(0.029)	(0.081)	(0.044)	(0.036)	(0.036)	(0.055)
Constant (control mean)	0.312***	0.275***	0.443***	0.281***	0.330***	0.309***	0.318***
	(0.018)	(0.020)	(0.044)	(0.027)	(0.024)	(0.020)	(0.035)
Observations	11,258	8,457	2,801	4,166	7,092	8,012	3,246
Lower bound estimate	0.186	0.207	0.083	0.111	0.224	0.142	0.228
	(0.031)	(0.039)	(0.099)	(0.063)	(0.041)	(0.054)	(0.057)
Upper bound estimate	0.259	0.270	0.212	0.258	0.258	0.262	0.247
	(0.028)	(0.031)	(0.084)	(0.042)	(0.038)	(0.041)	(0.054)
Panel B. Dependent variable: Probability of improving GPA in next term							
First year GPA < cutoff	0.099***	0.109***	0.061*	0.075***	0.111***	0.112***	0.070***
	(0.014)	(0.017)	(0.034)	(0.022)	(0.022)	(0.020)	(0.024)
Constant (control mean)	0.693***	0.680***	0.737***	0.680***	0.700***	0.691***	0.697***
	(0.009)	(0.011)	(0.020)	(0.013)	(0.014)	(0.011)	(0.019)
Observations	11,258	8,457	2,801	4,166	7,092	8,012	3,246

Notes: Estimated standard errors, clustered on GPA, are displayed in parentheses. Estimates are based on linear regression as described in Section IV, with rectangular kernel weights and a bandwidth of 0.6.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

be explained by the additional attrition caused by academic probation. In addition to having positive estimates for all of the lower bounds, Imbens and Manski's (2004) 95 percent confidence intervals do not include zero for any group except for the group of students with high school grades above the median.[31]

Finally, Table 5 shows estimated effects on the probability that students improve their grades. For students on probation, this outcome is crucial since it corresponds to the performance standard that they face and failure leads to suspension. The estimates demonstrate significant effects for all of the groups considered. Again, while the estimated bounds are not shown, these effects are too big to be attributed to nonrandom attrition induced by academic probation.

E. *The Impacts on Graduation*

We now consider the long-run effects of being placed on academic probation at the end of the first year. Since these outcomes are measured at a later date, it is important to keep in mind that some students who were in good standing after their first year have been placed on academic probation in subsequent evaluations.[32]

While it is relatively simple to analyze the impact of being placed on academic probation on the probability of graduation, it is difficult to unpack the various mechanisms that are set into motion by the treatment. The estimates in Section VC demonstrated that a sizable share of students around the threshold drop out of the university as a result of being placed on probation. If this were the only effect, then we would expect academic probation to either reduce the probability of graduating or, if the only students who drop out are those who would not have graduated regardless, to have no effect. However, if academic probation motivates the remaining students to improve their grades, as our estimates suggest in Section VD, then academic probation might increase the probability of graduating. Finally, academic probation might reduce the probability of graduation because it increases the probability of suspension, which likely increases the probability that a student drops out before finishing his degree.[33]

Figure 5 and column 1 of Table 6 show the estimated impacts on whether or not a student has graduated within four, five, or six years of their initial enrollment.[34] The estimates are consistently negative which suggests that being placed on academic probation at the end of the first year of college reduces the probability of graduating for the average student near the threshold, although these estimates are imprecise.

Columns 2–7 of Table 6 show the estimated impacts on graduation rates across different subgroups. Although we usually cannot rule out that the impacts are the

[31] In addition to selection bias, we have explored behavioral mechanisms that might explain the observed effects on GPAs. We find no evidence that being placed on probation causes returning students to enroll in easier courses, using average course grades as the measure of difficulty. On the other hand, we do find that being placed on probation reduces the number of units that students take in their second year by one-third of a credit (9 percent). However, some of this effect may be due to attrition midway through the second year.

[32] Further, some controls will have been suspended for poor performance in reported terms.

[33] The estimated effects on suspension can be found in prior versions of this paper.

[34] For these estimates, our sample is restricted to students in cohorts who are observed for at least four, five, or six years, respectively, whether they graduate or not. We have verified that the estimated impacts on graduation within four years and graduation within five years are similar when we use a consistent sample (of students who can be observed for at least six years).

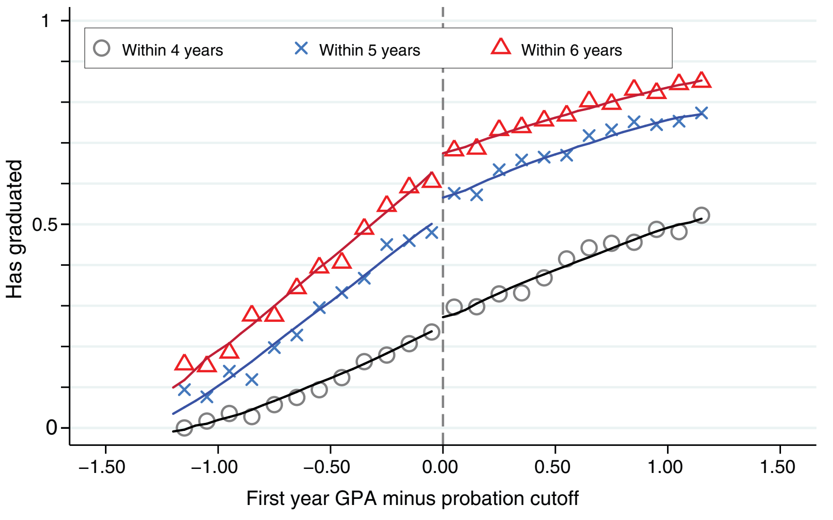

Figure 5. Graduation Rates

Notes: Each hollow circle is the mean of the outcome in an interval of 0.05 around the point (including the lower, but not the upper, endpoint). The curve is predicted from local linear regressions with a bandwidth of 0.6 using rectangular kernel weights.

same across the groups, the estimated impact on the probability of graduating within five or six years is strikingly large for students with high school grades above the median. For these students, being placed on probation after their first year reduces the probability of graduation within six years by 14.5 percentage points.[35] There are two primary reasons this effect is so large. First, the impact on dropping out at the end of the first year is relatively large for this group. Second, students with high school grades above the median who return to school after being placed on probation do not do any better than their counterparts with high school grades below the median. However, students with high school grades above the median who barely avoid being placed on probation in their first year perform relatively well in the long-run compared to their counterparts with high school grades below the median.

VI. Discussion

As a whole, the most striking feature of our results is the heterogeneity in students' responses to academic probation. Though probation approximately doubles the probability that males will leave school, it has no impact on female reenrollment rates. Similarly, probation more than doubles the probability that students who performed better in high school will leave school, but has little impact on the reenrollment decision of the students that performed worse in high school. Finally, being placed on probation increases the probability that native English speakers drop out by approximately 50 percent, but has no impact on students whose native language is

[35] Like the estimated impact on the probability of dropping out at the end of the first year, these estimates are greatest for males.

Table 6—Estimated Effects on Graduation

Relevant group	All (1)	HS grades < median (2)	HS grades > median (3)	Male (4)	Female (5)	Native English (6)	Nonnative English (7)
Panel A. Dependent variable: graduated after four years							
First year GPA < cutoff	−0.020	−0.019	−0.020	−0.045	−0.004	−0.047**	0.048
	(0.017)	(0.019)	(0.048)	(0.028)	(0.027)	(0.020)	(0.034)
Constant (control mean)	0.272***	0.265***	0.296***	0.214***	0.307***	0.277***	0.258***
	(0.011)	(0.015)	(0.034)	(0.020)	(0.012)	(0.012)	(0.023)
Observations	8,821	6,826	1,995	3,373	5,448	6,406	2,415
Panel B. Dependent variable: graduated after five years							
First year GPA < cutoff	−0.044*	−0.025	−0.113**	−0.055	−0.039	−0.065**	0.004
	(0.026)	(0.030)	(0.049)	(0.040)	(0.030)	(0.028)	(0.042)
Constant (control mean)	0.566***	0.550***	0.620***	0.503***	0.606***	0.552***	0.603***
	(0.018)	(0.023)	(0.028)	(0.030)	(0.018)	(0.018)	(0.029)
Observations	7,293	5,610	1,683	2,799	4,494	5,320	1,973
Panel C. Dependent variable: graduated after six years							
First year GPA < cutoff	−0.024	0.007	−0.145***	−0.081*	0.008	−0.041	0.007
	(0.024)	(0.028)	(0.053)	(0.042)	(0.031)	(0.030)	(0.045)
Constant (control mean)	0.674***	0.652***	0.760***	0.646***	0.693***	0.657***	0.726***
	(0.018)	(0.022)	(0.022)	(0.030)	(0.019)	(0.016)	(0.032)
Observations	6,005	4,649	1,356	2,313	3,692	4,417	1,588

Notes: Estimated standard errors, clustered on GPA, are displayed in parentheses. Estimates are based on linear regression as described in Section IV, with rectangular kernel weights and a bandwidth of 0.6.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

not English. At the same time, we find that being placed on probation improves the grades of returning students for all of the subgroups we consider.

These findings are consistent with the predictions of Bénabou and Tirole's (2000) model of performance standards. To review, the model predicts that introducing a performance standard will cause some agents to opt out (students to drop out) and improve the performance of those who remain (increase the grades of students who return). The model also predicts that those with the lowest ability should be most likely to drop out, where an agent's ability is defined as her probability of meeting the performance standard. Within the context of our analysis, this implies a student on academic probation makes the enrollment decision based on the probability of sufficiently improving her GPA, so as to avoid suspension. That is, students who are less likely to improve their GPAs should be more likely to drop out. Unfortunately, we cannot test this prediction with our data because we cannot observe the probability of meeting the performance standard for students that leave school.

Because the model focuses on students' abilities to meet the performance standard, it would explain the heterogeneity that we observe in those terms. That is, the large discouragement effect for students who performed best in high school, males, and native English speakers, would reflect that students in these groups have relatively low probabilities of improving their grades upon returning to school after being placed on probation. At the same time, differences in how these students update their self-perceived abilities might also explain their different responses. For example, even if they are of higher ability, students with higher high school grades might be more likely to drop out after being placed on probation because they update self-perceived ability by a greater amount. The differences we observe might also be driven by differences in risk aversion, costs of effort, or returns to education. All of these explanations are speculative, however, and further research is needed to identify what underlies these differences. We should also note that it is not a given that students who performed best in high school, males, and native English speakers, are reacting too strongly to being placed on probation. Females, students that performed worse in high school, and nonnative English speakers may be reacting too little.

VII. Conclusion

Overall, our results support Bénabou and Tirole's (2000) model of performance standards. We confirm that a performance standard has a discouragement effect (causing students to drop out of school) and an encouragement effect (improving the grades of returning students).[36]

Consistent with a sizable literature on gender differences in students' responses to positive incentives, we find substantial gender differences in response to a *negative* incentive. We find that academic probation doubles the probability that men drop out, but has no such effect on women. We also find evidence that being placed on probation improves the grades of those that return for individuals of both genders.

Ideally, a performance standard might just "weed out" those who have no chance at success and serve as a motivation for others.[37] We do find positive effects on the subsequent GPAs of students who continue to enroll. In our setting, we might hope the standard would improve graduation rates. Instead, our results suggest that being placed on probation at the end of the first year of college reduces the probability that a student graduates. The impact is especially strong for students with high school grades above the median for whom it reduces the probability of graduation by approximately 14.5 percentage points. This effect is so large that these students are no more likely to graduate than students with high school grades below the median.

Our results have important consequences for the wide variety of circumstances in which standards might be applied as a means of improving performance. We confirm that a performance standard can entail a trade-off between causing some to improve and causing others to give up. Further, our results indicate that introducing a performance standard is particularly effective in motivating women and students with relatively low high school grades. On the other hand, concerns about discouragement are especially relevant for men and those with the highest levels of prior academic performance.

[36] As we alluded to in the introduction, concerns about student discouragement are often raised in discussions about high school exit exams, another example of an educational performance standard.

[37] While it is possible that the university wants to weed out students who are a poor fit, conversations with administrators suggest the policy is aimed solely at promoting student achievement. The encouraging letter sent to students who are placed on probation further supports this administrative stance.

Appendix: Letter Sent to Students at Campus 2

Dear < first name >:

Your academic record indicates that you are experiencing challenges with your studies at xxxxxxxxxxx. As a result, you have been placed “On Probation” at the end of the xxxxxxx 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.xxxxxxxxx. Second, contact xxxxxxxx for assistance with study habits, note taking, effective research, time management, study groups, and peer mentors. Finally, the xxxxxxxxx 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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