The Disparate Impacts of Academic Probation

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Abstract

Academic probation is a policy affecting 10 to 20 percent of all first-year U.S. college students. This paper provides the first evidence on the role of academic probation in widening socioeconomic gaps in educational attainment. Our setting is a large public university in California, where first-year students are placed on academic probation if their GPA falls below a 2.0. Using a regression discontinuity design, we find that being marginally placed on academic probation has no significant impact on first-year GPA, but does significantly increase low-income students' first year dropout rate. Low-income students are also 22.8 percentage points less likely to graduate within 6 years. High-income students are largely unaffected by academic probation placement. We next examine whether an alternative academic probation policy can limit these negative effects. Later cohorts at this university are placed on academic probation and required to participate in a coaching program if their GPA is below a 2.0. We find that both low- and high-income students do not experience a deterioration in their first-year dropout or graduation rates, and significantly improve their GPA as a result of this alternative policy. Our findings highlight that while universal academic probation widens socioeconomic gaps in degree completion, combining probation with coaching can counteract these effects.

1 Introduction

Income mobility in the United States has declined significantly over the past century, with children today only half as likely to earn more than their parents compared to those born in the 1940s. This decline is partly due to disparities in higher education attainment, as a college degree remains a critical path to upward mobility (Chetty et al., 2020). While the labor market returns to a four-year degree are substantial and have grown over time—especially for low-income students (Zimmerman, 2014; Smith et al., 2020)—a significant gap persists in college completion rates between students from high- and low-income families. Among children from the bottom quartile of the income distribution, only 9% complete a bachelor's degree by age 25, compared to 54% of children from the top quartile (Bailey and Dynarski, 2011). This disparity perpetuates income inequality and restricts social mobility for those from lower-income backgrounds.

Chetty et al. (2020) find that when students from diverse socioeconomic backgrounds graduate from the same college, their post-college earnings align more closely, suggesting that colleges can serve as an equalizing force. Based on this finding, they propose that reshaping college admissions processes could significantly reduce economic segregation and improve intergenerational mobility. However, the scalability and feasibility of such admissions-focused reforms are limited, especially since lower-income students often face additional, non-financial barriers to completion that persist even after admission (Dynarski et al., 2022). This highlights the need to examine existing institutional policies and features that may hinder social mobility so that universities can better shape interventions to expand access, improve retention, and enhance equity across income groups.

This paper documents the role of an important higher education policy, academic probation, in exacerbating socioeconomic disparities in college completion. Academic probation serves as a label or warning to students who fail to meet minimum grade point average (GPA) requirements. It is a near-universal policy that affects an estimated 10 to 20 percent of first-year students at U.S. colleges (Staley, 2022). Considering that 61.4 percent of recent U.S. high school graduates enroll in college (BLS, 2023), this policy has broad reach and the potential to substantially influence social mobility. We then ask whether an alternative probation policy that incorporates coaching can counteract the socioeconomic gaps in academic outcomes caused by the standard probation policy.

Our setting is a large and selective public four-year college in California. Prior to 2009, the university had a standard academic probation policy in which underperforming first-year students were simply notified of their probation status and warned that they needed to raise their GPA to be taken off probation. In an effort to improve retention rates, the university implemented an alternative probation policy in 2009. Under the new policy, students were still notified of their probation status but were also required to enroll in a university-run coaching program. Program participants attend a two-hour workshop led by trained faculty and staff coaches. Students are provided with role models and encouragement through watching a video of successful individuals

who overcame setbacks, and coaches share with students their own experiences with failure. The workshop is conducted in a group setting to reinforce that students are not alone in being on academic probation. Coaches lead goal-setting and time management exercises to help students identify their challenges and develop an action plan. Students also receive information about campus resources and the academic probation policy to help reduce the anxiety and uncertainty associated with the probation label. After the workshop, students are required to either use a campus resource or meet one-on-one with their coach.

We collect rich administrative data on students who first enrolled at this university from the years 2007 to 2017. Our data allow us to observe students in each quarter they are enrolled at this university and thus, estimate how each of the probation policies affects their academic performance, persistence, and likelihood of graduation. Both before and after 2009, freshman students are placed on academic probation if their first-quarter GPA is below a 2.0. To estimate causal effects, we use a regression discontinuity design (RDD) where we compare outcomes of students who score marginally below this threshold and are placed on probation, to those whose GPA is marginally above and who are not placed on probation. We run two separate RDD analyses. The first focuses on students who first enrolled at the university prior to 2009 and captures the impacts of the standard academic probation policy (henceforth, "standard academic probation"). The second uses later cohorts and shows the effects of combining academic probation with coaching (henceforth, "academic probation + coaching").

Our findings indicate that the standard academic probation policy substantially discourages students. In the full sample, probation has no significant effect on first-year GPA, but significantly increases first-year dropout rates by 10.9 percentage points. It also reduces 6-year graduation rates by 8 percentage points, but this estimate is not statistically significant at conventional levels. Our results further reveal that the standard probation policy substantially widens socioeconomic gaps in academic outcomes. While high-income students' outcomes are largely unaffected, low-income students seem to bear the full costs of the standard probation policy. Low-income students are 11.4 percentage points more likely to drop out after their first year and 22.8 percentage points less likely to graduate within six years due to placement on academic probation.

Turning to later cohorts, we show that a probation policy that incorporates coaching improves academic performance and does not negatively impact degree completion. Overall, placement on academic probation with coaching significantly improves first-year GPA by 0.242 standard deviations. Both low- and high-income students benefit, increasing their GPA by 0.308 and 0.208 standard deviations, respectively. Probation with coaching also has no significant effects on first-year dropout or 6-year graduation for both low- and high-income students. Assuming that the negative effects of the standard probation policy remain constant over time, these results suggest that the coaching program closes the socioeconomic gap in academic outcomes caused by the traditional probation policy.

Our paper is the first to show that a universal higher education policy—academic proba-

tion—substantially widens socioeconomic gaps in college degree completion. Prior research has highlighted how institutional resources and supports, such as higher per-student spending (Bound et al., 2010; Deming and Walters, 2017), financial aid and loan availability (Black et al., 2022; Dynarski et al., 2022), and targeted academic support programs (Barr and Castleman, 2018; Clotfelter et al., 2018; Canaan et al., 2022), improve student success. Much less attention has been paid to institutional policies that may unintentionally undermine persistence. For example, Bleemer and Mehta (2022) show that GPA-based major restrictions reduce underrepresented minority enrollment, and Ost et al. (2018) find that dismissal policies for low-performing students lower BA completion and later earnings. We contribute to this line of work by focusing on academic probation, a widespread but less severe policy that serves as a warning rather than immediate dismissal.[1]

Previous studies have also documented that academic probation leads to discouragement effects. In their seminal work, Lindo et al. (2010) find that among Canadian college students, probation increases first-year dropout rates and reduces degree attainment, with effects concentrated among high-ability students, men and native English speakers. In the U.S., Fletcher and Tokmouline (2018) and Casey et al. (2018) show that placement on probation has no impact on students' dropout rates but improves their GPA in subsequent terms. On the other hand, Dong (2019) finds that probation increases university dropout rates for women but not for men in Texas.

We make two contributions to this literature. First, we provide the first evidence that standard academic probation policies exacerbate socioeconomic disparities in college persistence and completion. Second, we show that pairing probation with a mandatory coaching program eliminates these adverse distributional effects and improves academic performance. Taken together, our findings highlight that widely used policies can unintentionally exacerbate inequality, but also that relatively modest design changes can transform them into effective supports.

2 Institutional Setting

Our setting is a large, selective, public 4-year university located on the Central Coast of California. The university serves approximately 21,000 students, with a focus on undergraduate education, particularly in engineering and agriculture fields. For the 2019–20 academic year, the undergraduate acceptance rate was 28%, and tuition and fees (excluding books, supplies, room/board, etc.) totaled nearly $10,000/year for California residents and $25,000 for out-of-state and international students. The 2019 first-time freshmen entering cohort had an average high school GPA of 4.1 (on a 5.0 scale), an average SAT score of 1,375 (among the top 20% nationally) and an average ACT score of 29. The university operates on a quarter calendar where three eleven-week terms make up the academic year: fall, winter and spring quarters.

[1] In our setting, students on probation have two quarters to raise their GPA and avoid dismissal.

2.1 Academic Probation

Academic probation is a near universal policy in US postsecondary institutions. Probation is a warning or label given to students who score below a minimum GPA threshold. At this university and similar to other institutions, academic probation is solely a function of a student's GPA. At the end of each quarter, students whose cumulative or term GPA is less than 2.0 are placed on academic probation and notified of this status by email. Students remain on probation until their term and cumulative GPAs are above the 2.0 threshold. First-year student who fail to meet this mark by the end of their first year are subject to dismissal and are not eligible to return for their second year.[2]

Academic probation is a well-intentioned policy as it is meant to serve as a wake-up call for capable students who are underperforming, and to weed out students who are "mismatched" and would be better off going to a less selective university. However, a major concern is that probation may unintentionally weed out capable students who are discouraged by this label. Indeed, models of intrinsic and extrinsic motivation predict that such a policy has a discouragement effect, as students may interpret the probation label as a negative signal of their ability, which in turn lowers their self-confidence, motivation, and performance (Bénabou and Tirole, 2003). This concern is particularly salient for lower-income students as they often face barriers to degree completion that their higher-income counterparts do not. This begs the natural question: Who exactly is bearing the brunt of the unintended consequence of this widely applied policy?

2.2 Coaching Program

In 2009, the university introduced a mandatory academic coaching program for first-time freshmen who are placed on academic probation at the end of the fall quarter of their first year. The program was introduced because of concerns that probation may be ineffective or discourage students. It was designed to take a different approach from the standard academic probation corrective measure, and its curriculum is based on psychologist Dr. Albert Bandura's Theory of Self-Efficacy (Bandura, 1977). The theory posits that individuals with sufficient levels of self-efficacy have confidence in their ability to exert control over their motivation and behavior and, consequently, are able to achieve specific performance benchmarks. As such, the coaching program aims to improve self-efficacy.

The program was first implemented as a pilot in the fall of 2009 for four of the university's six colleges, and was extended to the entire university the following year. Starting in 2009, students who earn below a 2.0 GPA in their first fall quarter at the university, are placed on probation and are required to complete the coaching program during the winter quarter. The program consists of two parts: (1) a two-hour workshop led by faculty coaches in the first two weeks of winter quarter, and (2) a mandatory campus engagement assignment due by week 5, which includes a reflection

[2]Students who are placed on academic probation in any other quarter than Fall, are granted only one quarter to improve their academic standing above the 2.0 threshold before being eligible for dismissal.

exercise and either a campus visit or a follow-up meeting with the coach. The university typically offers two workshop dates during the first weeks of the winter quarter to accommodate student and faculty schedules. Roughly 320 students qualify for the program each fall quarter, and almost all of them participate in one of the two workshop sessions. A small share of students are unable to attend the session due to a scheduling conflict and complete the requirement one-on-one with a trained coach. To enforce participation, students are unable to enroll in spring quarter courses until they have completed all parts of the program.

The coaching program was designed to expose students to information sources in a way that boosts self-efficacy. The first part of the two-hour workshop is a 30-minute meeting with all session participants (typically about 150 students) which aims to normalize failure and academic probation by showing students they are not the only ones who have experienced failure and can still succeed. As such, students watch a video featuring various high-profile people in Silicon Valley who have overcome challenges and failure. To reduce anxiety surrounding probation—which can lower self-efficacy—members of the program's leadership team also share key campus resources including tutoring, health, and counseling services (see Section D) and explain academic probation rules.

The second part of the workshop is meant to be more interactive and discussion-based. It involves a breakout session with a smaller group, typically 6–8 students, led by one or two trained coach. Coaches are faculty and staff from across the university who have undergone a two-hour training led by the program's leadership team.[3] In an attempt to reiterate the message that failure is common among successful people, the session opens with coaches sharing a time when they experienced failure. The coaches then facilitate a reflection and goal-setting exercise. Students are allotted time to reflect on factors that may have contributed to their academic struggles during their first quarter, such as academic challenges (e.g., problems with time management, study skills, or school/life balance); college adjustment difficulties (e.g., difficulty finding resources or fitting in); and personal hardships (e.g., mental health issues, personal or family crises, or identity-based isolation). To guide this process, participants work through a worksheet, pausing to discuss their responses with the group. The worksheet, presented in Section D, is set up in three steps: identifying weaknesses, identifying solutions or resources that can aid in overcoming these weaknesses, and goal-setting for the current quarter. The intent of this exercise is for students to leave the workshop with a tangible plan to change their academic trajectory going forward. During this time, participants are also required to complete a time management worksheet in which they are encouraged to allocate time for classes, studying, and social activities (Section D). Finally, throughout SP, students are exposed to encouragement and positive feedback from coaches.

[3]Faculty and staff who become coaches select into this service role. Faculty receive service credit from their home departments for their participation, and staff's time spent on coaching is considered part of their typical work day.

3 Data

Our main student-level data are administrative records taken from the university's Office of Institutional Research. These files follow each student by quarter through graduation or until they separate from the university, and provide detailed information on students' academic progress. The complete sample includes eleven first-time freshmen cohorts who enrolled at the university in a fall quarter between 2007 and 2017. We merge these data with coaching program participation files to identify students who completed the coaching program. In an auxiliary analysis, our baseline data are augmented with labor market outcomes from the California Employment Development Department which we describe in **??**. We also access pre- and post-coaching survey responses from the coaching program office to provide evidence on mechanisms, and we discuss these in detail in **??**.

Our analysis first documents the impacts of academic probation placement (henceforth "probation-only") then examines how offering the coaching program along with probation (henceforth "probation + coaching") affects student outcomes. For the former analysis, we focus on students who entered university in the years 2007 to 2009. We exclude all cohorts of students enrolled after 2009 because the coaching program was rolled out across the entire university in 2010 and was administered based on the same 2.0 GPA probation threshold. Additionally, for the cohort of students entering university in the year 2009, we only include students enrolled in the College of Science and Mathematics and College of Liberal Arts as students in other Colleges were exposed to the coaching program as part of a pilot program.[4] When looking at the impacts of offering coaching with probation, we focus on entering cohorts from fall 2010 to fall 2017, along with the 2009 entering cohort in colleges that were part of the coaching pilot program.

The first panel of Table 1 shows summary statistics for students' baseline characteristics. Column (1) reports these for our "probation-only" cohorts which contain 8,632 first-time, full-time enrolling students. Column (2) restricts the probation-only sample to the 4,595 students with a GPA between 1.0 and 3.0 at the end of the first quarter at the university—that is, those whose GPA is marginally on either side of the 2.0 threshold or our main regression discontinuity (RD) sample. Students who enrolled at university between the years 2007 and 2009 scored an average of 628 points on the SAT Math exam (Column (1)), while those with a GPA between 1 and 3 performed relatively worse with an average of 615, as shown in column (2). Additionally, 47 and 33 percent of students in the full sample are female and non-white respectively, while these proportions are 42 and 37 percent for students in the RD sample. The proportion of Pell Grant eligible students is low for both samples. Column (3) focuses on all students in the later cohorts who were exposed to both probation and coaching (37,266 students), and Column (4) restricts this sample to those who have a GPA within 1.0 to 3.0 at the end of their first quarter (17,528 students). "Probation + coaching" marginal students have a lower average Math SAT score (of 636) than the overall sample

[4]The university is divided into six colleges or faculties: Agriculture, Food, and Environmental Sciences; Business; Engineering; Architecture and Environmental Design; Science and Mathematics; Liberal Arts.

(with a score of 653). 45 and 44 percent of the marginal sample are female and non-white versus 48 and 39 percent for the whole sample, and around 80 percent have highly educated parents.

The second panel of Table 1 reports summary statistics for our main academic outcomes. For both the "probation-only" and the "probation + coaching" cohorts, our marginal samples have worse average first-year GPA (2.46 in Column (2) and 2.55 in Column (4)) than the overall samples (2.76 for Column (1) and 2.9 for Column (3)). One of our main outcomes of interest is dropping out at the end of the first year. This outcome takes the value of 1 if a student does not appear in the data the following academic year, and 0 otherwise. While 9 percent of students in the full "probation-only" sample are likely to drop out at the end of the first year, those in the RD sample are 1 percentage points more likely to do so. In the "probation + coaching" cohorts, the first-year dropout rate is 6 percent for the full sample and 8 percent for the marginal sample. We also find meaningful long-term differences as 80 percent of students in the full "probation-only" sample end up graduating within 6 years, while only 74 percent of students in the marginal sample do so. The 6-year graduation rate is higher for the "probation + coaching" cohorts and stands at 88 percent for the full sample and 83 percent for the marginal sample. For all our academic outcomes, students in the "probation + coaching" cohorts are better off than those in the "probation-only" cohorts suggesting that coaching may help retain students on probation.

4 Identification Strategy

4.1 Regression Discontinuity Design

We analyze the impacts of two separate policies on student outcomes. The first is the policy of placing students on academic probation, while the second is offering coaching in tandem with academic probation. For both policies, we use a regression discontinuity design to estimate their causal effects. This is possible because prior to 2010, students who scored below a 2.0 GPA at the end of their first quarter were placed on probation, while students scoring at or above this cutoff were not. For subsequent cohorts, students who scored less than 2.0 GPA at the end of their first quarter were placed on probation and assigned to coaching, while those who scored above the threshold were not.

The key identifying assumption underlying our design is that all determinants of future outcomes vary smoothly across the threshold—a point we return to in Section 4.2. If this holds, then we can attribute any mean difference in outcomes between the treatment (students who score just below the 2.0 GPA) and control (students who score 2.0 or just above) groups to be the causal effect of academic probation placement for the pre-2010 cohorts. For the later cohorts, this would be the causal effect of probation along with coaching.

Formally, we estimate the following reduced-form equation:

$$Y_{ic} = \alpha + g(S_{ic}) + \tau D_{ic} + \delta X_i + \gamma_c + \mu_k + \epsilon_{ic} \tag{1}$$

Y_{ic} represents either outcomes for student i in cohort c. D_{ic} is a dummy variable indicating whether student i is below the cutoff of 2.0. S, our running variable, represents students' first quarter GPA relative to the 2.0 cutoff. The function $g(.)$ captures the underlying relationship between the running variable S_{ic} and the dependent variable Y_{ic}. We also allow the slopes of the fitted lines to differ on either side of the admissions threshold by interacting $g(.)$ with the treatment dummy D. X_i is a vector of student baseline covariates that should not significantly change the treatment estimate if our identifying assumption holds. Additionally, we include cohort or year fixed effects γ_c to account for cohort-specific shocks as well as college (i.e. faculty) fixed effects μ_k throughout. ϵ_{ic} represents the error term. Finally, the parameter τ gives us the causal effect of the policies.

We follow the convention in the literature by specifying $g(.)$ to be a linear function of S using local linear regressions with a triangular kernel. This approach has the benefit of generating estimates that are more local to the threshold without imposing any strong functional assumptions on the data. Our preferred specifications are drawn from local linear regressions using the MSE-optimal CCT (Calonico et al., 2014) bandwidth selector to determine the range (bandwidth) of data used for each regression. Note that because the CCT bandwidth selector predicts different bandwidths depending on outcome, the number of observations in each regression may vary slightly from one outcome to another. However, as a robustness check, we also present graphical results for a range of overlapping bandwidths for all outcomes of interest. Finally, we report robust standard errors throughout (Kolesár and Rothe, 2018).

In Figure 1, we show that both policies are binding in practice. These figures are our "first stage" RD regressions and take the same form as those after, in that scatter points represent local averages of the outcome over a 0.1 GPA range and are reported using a bandwidth of 1 GPA point on either side of the cutoff. Figure 1a reports the likelihood of being placed on probation as a function of Q1 GPA for cohorts entering the university in Fall of the years 2007, 2008 and faculties that were not part of the coaching program pilot in 2009. The figure shows that all students scoring below the cutoff are placed on probation and all those scoring above are not, which lends itself to a sharp RD design. Figure 1b reveals that the probation label was also fully binding for the cohorts exposed to coaching. Figure 1c plots the likelihood of coaching program participation by first quarter GPA for all entering cohorts from fall 2010 to fall 2017.[5] A sharp jump in the likelihood of coaching program participation is visible at the 2.0 GPA threshold. No student with a first quarter GPA above the threshold participates in coaching while virtually all students scoring below the 2.0 cutoff participate.[6]

[5] We exclude from this figure students from the few faculties who were selected for the SP pilot in 2009 as we do not have program participation data for them.

[6] Each fall quarter there are a few students (less than 10) who qualify for the SP but who are granted a waiver by the dean of their college and are thus excused from participating. These waivers are typically reserved for extenuating circumstances such as health shocks or family emergencies.

4.2 Threats to Identification

A standard concern with any regression discontinuity design is the ability for individuals to precisely control the running variable. In our setting, this can occur if students are able to precisely manipulate their GPA around the cutoff, leading to differences in unobserved determinants of outcomes near the threshold. Note that this requires precise control around the cutoff which is distinct from motivated students expanding more effort in general. Our running variable, first-quarter GPA, is the average of three or four courses which makes it difficult to precisely control. Nonetheless, we conduct empirical checks to alleviate any concerns that unobserved attributes of students just above and just below the cutoff differ.

The first informative test is to check for jumps in the distribution of the running variable at the cutoff (McCrary, 2008). If students are able to precisely control their first-quarter GPA, then we would expect to observe a mass of students just above the probation cutoff of 2.0 preceded by a dip just before. However, a continuous running variable is neither a sufficient nor necessary condition for identification. Indeed, this test may not be as helpful if discontinuities in the distribution of the running variable can be attributed to exogenous factors such as grade rounding—which commonly occurs with GPA at US postsecondary institutions (see Zimmerman (2014); Ost et al. (2018)).

Figure 2a and 2b shows the first-quarter GPA distribution of all students in the probation only cohorts as well as the probation with coaching cohorts, respectively. The distributions mirror those found in studies by Zimmerman (2014) and Ost et al. (2018) with heaps in the GPA distribution. Notably, in addition to the heap at the 2.0 cutoff, we observe distributional discontinuities at GPA values of 1 and 3—as shown by the scatter points just above the vertical dashed lines in the figures. While the 2.0 GPA cutoff is considered "high-stakes" in our setting, GPA values of 1.0 and 3.0 carry no special or significant designation and are thus not considered "high-stakes". Hence, these distributional discontinuities are most likely due to the number of combinations resulting in whole-number GPAs being larger than those for decimal GPAs, especially when measured after only one quarter.

To further validate that the observed pattern of grade distributions is not the result of strategic sorting, we test for potential imbalances in student predetermined characteristics. For each of our "probation only" and "probation + coaching" cohorts, we regress the likelihood of 6-year graduation on our baseline covariates. We then plot the resulting predicted values as a function of the running variable in Figures 2c and 2d. We consider covariates that are known to be good predictors of future outcomes: Math and verbal SAT scores, gender, race, remedial course requirements, Pell grant eligibility, financial aid eligibility and whether a student's father or mother went to college. The running variable is defined as the number of GPA points above or below the probation threshold. Figures 2c and 2d show that the predicted graduation rates are smooth at the threshold for both the probation only and the probation + coaching cohorts—indicating that baseline covariates are balanced at the threshold. We also show how threshold-crossing affects each of the aforementioned baseline characteristics in Appendix Table A1. Local linear RD estimates reported in the table

are based on bandwidths of 0.5 and 0.75 for each outcome. Notably, 8 out of the 9 outcomes are statistically insignificant at conventional levels. This is in line with our identifying assumption and is also consistent with the premise that any observed discontinuities in the distribution of the running variable are not the result of strategic sorting on the part of students or administrators. Thus, any documented discontinuities in outcomes can be attributed to the probation policies.

5 Results

5.1 Impacts on Academic Outcomes

We begin by examining the impacts of "probation only" and "probation + coaching" policies on students' academic outcomes. Figure 3 presents regression discontinuity (RD) plots for our academic outcomes, with first-quarter GPA as the running variable. Figures on the left show effects at the 2.0 GPA cutoff for students in cohorts exposed to probation-only policy, while those on the right present effects for cohorts exposed to probation + coaching.

Figure 3 provides visual evidence of meaningful differences between students exposed exclusively to academic probation and those exposed to probation with coaching. In Figure 3a, being placed solely on academic probation has no significant impact on first-year GPA. In contrast, probation with coaching noticeably boosts students' GPA, as we see a clear discontinuity at the cutoff. Table 2 reports RD estimates of the effect of each policy on our academic outcomes using the CCT bandwidth selector. Consistent with the visual evidence, placement on academic probation only has no significant effect on GPA, while probation combined with coaching significantly boosts first-year GPA by 0.242 standard deviations (Column (1) of Table 2). Figure 3c and Column (2) of Table 2 further reveal that students who just qualify for only probation are 10.9 percentage points more likely to drop out by the end of the first year compared to those who just avoid probation. This large and meaningful gap at the cutoff is greatly reduced to a statistically insignificant 2.8 percentage points for cohorts exposed to probation with coaching. Under the assumption that the effects of probation are similar for all cohorts, this suggests that the coaching program can counteract the negative impacts of probation on dropout rates.

In Figure 3e and Figure 3f, we find no visual evidence that either probation-only or probation with coaching changes students' probability of graduating on time. In contrast, Figure 3g suggests that students in probation-only cohorts with a GPA just below the threshold are less likely to graduate in 6 years. The corresponding estimate in Column (4) of Table 2 indicates an 8 percentage point drop in 6-year graduation but is not statistically significant at conventional levels. For probation with coaching cohorts, both Figure 3h and the corresponding estimate in Column (4) of Table 2 reveal that threshold-crossing has no significant impact on 6-year graduation.

Our RD regressions so far use bandwidths chosen by the CCT optimal bandwidth selector. As a robustness check, we show that our estimates are not sensitive to bandwidth choice in Appendix Figures A1. The different figures show RD estimates for all outcomes across bandwidths ranging

from 0.25 to 1 GPA point, alongside their corresponding upper and lower 95% confidence intervals. The figures on the left are for probation-only cohorts, while the ones on the right are for cohorts exposed to both probation and coaching. Consistent with our main estimates, first-year GPA remains statistically insignificant regardless of bandwidth choice for the probation-only cohorts. For the probation + coaching cohorts, the GPA estimates are consistent with our main results and significant across all bandwidths. The estimates on first-year dropout in the probation-only cohorts are more or less stable, hovering around the 8 percentage point mark for bandwidths greater than 0.4 GPA points. In contrast, threshold-crossing has an insignificant impact on dropout for probation + coaching cohorts regardless of the chosen bandwidth. In both cohorts, estimates for six-year graduation are not statistically significant. Nonetheless, in the probation-only cohorts, they are remarkably stable and hover around an 8 percentage point reduction.

5.2 Effects by socioeconomic background

Our overall effects may mask contextual heterogeneity, as probation may be particularly harmful to low-income students who have less access to resources and information. Indeed, parental income tends to be highly correlated with student success and evidence from the literature suggests that low-income students, in particular, make sub-optimal decisions in educational settings (Roderick et al., 2008; Bowen et al., 2009; Smith et al., 2013). We therefore examine heterogeneous effects by student family income. We identify low-income students as those eligible for federal financial aid i.e., students with an expected family contribution (EFC) score that is less than $30,000, while higher-income students are those ineligible for federal aid.

The different panels in Figure 4 plot our academic outcomes as a function of the running variable for low-income students. Figures on the left document the effect of the probation-only policy, while those on the right look at probation with coaching. Figure 5 presents similar plots but for high-income students. The general pattern emerging from these figures is that low-income students seem to bear the brunt of the negative effects of academic probation. While probation only has no significant effect on first-year GPA, the discontinuity at the cutoff in Figure 4c indicates that it does increase first-year dropout rate for low-income students. For high-income students, first-year dropout in Figure 5c looks more smooth at the cutoff. Corresponding RD estimates are reported in Column (2) of Table 3 and are consistent with the visual evidence: low-income students are 11.4 percentage points (significant at the 10% level) more likely to dropout after their first year as a result of probation, while the estimate for high-income students in insignificant at conventional levels. For both low- and high-income students, probation does not affect 4-year graduation rates. On the other hand, academic probation significantly reduces low-income students' 6-year graduation rates in Figure 4g. In Column (4) of Table 3, the magnitude of this drop is on the order of 22.8 percentage points, while this estimate is insignificant for high-income students. Overall, this analysis indicates that the standard universal probation policy substantially penalizes low-income students, and widens the socioeconomic gap in college completion.

Turning to academic probation with coaching, effects for both low- and high-income students are consistent with the overall pattern. In Figures 4b and 5b, requiring coaching in tandem with academic probation significantly improves both low- and high-income students' first-year GPA. Column (1) of Table 3 indicates this improvement is on the order of 0.308 and 0.208 standard deviations for low- and high-income students, respectively. Conversely, for both low- and high-income students, being marginally on either side of the probation + coaching cutoff has no significant effects on any of the other academic outcomes.

While low- and high-income students do not seem differentially impacted by the offer of probation with coaching, there are still some subtle differences in the interpretation of these effects. High-income students are for the most part unaffected by either probation or probation + coaching. On the other hand, placement on probation has substantial negative effects on low-income students' academic outcomes. The fact that probation combined with coaching does not affect these students' dropout or graduation rates suggests that coaching effectively counteracts the negative impacts of probation alone. Therefore, a probation policy that includes coaching could be key to closing the socioeconomic achievement gap caused by the standard universal probation policy.

6 Discussion

This paper shows that the standard universal academic probation policy widens socioeconomic gaps in college dropout and degree completion. We further find that academic probation combined with coaching has no significant effects on low- and high-income students' dropout and degree completion, and even improves their first-year academic performance. Assuming that the impacts of probation only do not significantly change across cohorts, this indicates that the offer of coaching counteracts the negative impacts of the universal probation policy. In this section, we discuss potential mechanisms behind our effects.

6.1 Discouragement Effects of the Standard Probation Policy

We start by providing possible explanations for the standard academic probation policy's effects. As previously discussed by Lindo et al. (2010), when a university places a student on academic probation, it is effectively imposing a performance standard, as the student has to raise her GPA sufficiently to be taken off probation. They argue that consistent with Bénabou and Tirole (2000) model of performance standards, academic probation is predicted to discourage some students from persisting at the university. A key contribution of our paper is to pinpoint that the group of students most discouraged by probation are those from low socioeconomic backgrounds.

Why are low-income students disproportionately discouraged by academic probation? Previous studies have identified behavioral patterns that low-income students may be particularly prone to (see Dynarski et al. (2022) for a summary) and that could lead them to be particularly discouraged by a policy like academic probation. One of those behaviors is debt aversion, in which low-income

students may be particularly reluctant to take out loans to pay for college. In our setting, this could be an issue if students lose financial aid as a result of academic probation. At this university, students become ineligible for federal and state need-based aid (such as Pell Grants or Cal Grants) if their cumulative GPA at the end of their first year is below a 2.0. Consequently, to assess this mechanism, we employ an indicator for scoring below a 2.0 cumulative GPA at the end of first year as an outcome variable. The RD estimates, which are presented in column (1) of Appendix Table A2, are large and positive, especially for low-income students, but have large confidence intervals. While we do not find strong evidence in favor of this mechanism, given the lack of statistical power and the large magnitudes, we are limited in the conclusions we can draw from this exercise.

Low-income students, in particular, may lack information or awareness about educational options, leading to suboptimal decisions (Lavecchia et al., 2016). In this case, higher-income students may have more information on how to strategically get out of academic probation by "adjusting" their majors, rather than dropping out entirely like their lower-income counterparts. Column (2) of Table A2 reports RD estimates for the outcome, 'switch major', which takes on a value of 1 if a student ever switches majors and 0 otherwise. The results indicate that this is not an important dimension in our context as probation is not inducing low- or high-income students to switch majors.

Other behaviors than can explain the differential impacts of academic probation are present bias, loss aversion, negative social identity and feeling out of place (Lavecchia et al., 2016; Dynarski et al., 2022). Due to present bias, students may put too much emphasis on the short-term costs of academic probation—such as the effort required to raise their GPA and get out of probation—and not enough on the long-term gains of graduating from the university. Loss aversion suggests that students may react more strongly to losses relative to equivalent gains. Academic probation may be perceived as a loss, as it signals to students that they are failing to meet performance standards. Students may also wish to avoid future academic losses by dropping out of the university. Importantly, these behavioral patterns are particularly salient among low-income students (Dynarski et al., 2022). Finally, students often make choices that are in line with their social identity and the behavioral expectations of their closest social group. Low-income students, who often lack examples of college graduates in their immediate social networks, may feel out of place during their first year of college and interpret academic probation as confirmation that they do not belong.

6.2 Why Does Coaching Counteract the Negative Effects of Academic Probation?

We next discuss why coaching may mitigate the negative effects of academic probation for low-income students. The coaching program in our setting has multiple components that may make it particularly useful for addressing behavioral barriers to low-income students' academic success. First, the overall message that the program conveys to students is that they are not alone in being on academic probation and that they can still succeed despite this setback. In practice, this

message is communicated through conducting the program in a group setting, showing students videos about successful individuals who have previously failed, and having coaches share their personal experiences with failure. These elements target negative social identity by reducing the isolation that academic probation creates, which often leads students to feel like failures. The video and coaches further provide role models who have succeeded despite setbacks, which are typically missing from low-income students' social groups. Second, coaches provide students with information about probation and campus resources, assist them with time management and goal-setting exercises, and students are required meet one-on-one with a coach or a campus resource. Goal-setting and time management can address present bias by helping students focus on long-term goals rather than immediate costs. Providing students with information about probation and campus resources may help close the information gap about educational options that exists between high- and low-income students.

We next provide suggestive evidence on which components of the program are most effective in counteracting the negative effects of academic probation. Because it is difficult to address this empirically, we use Bénabou and Tirole (2003)'s model of extrinsic and intrinsic motivation to generate theoretical predictions regarding which element of the program is expected to be most beneficial in Appendix C. The model is a game between two players: the principal or the university and the agent or the student. The student, who has imperfect information about her ability, is offered an incentive structure by the university in order to get her to undertake a task such as increasing her grades or persisting at the university. In the model, we classify the different components of the program into one of two incentive structures: help and encouragement. Help includes all components of the program that aim to assist students in some way. These comprise giving students information about campus resources and academic probation, coaches walking them through the time management and goal-setting exercises and initiating students' use of campus resources. On the other hand, components which aim to communicate to students the message that it is still possible to succeed despite failure are classified as encouragement.

The model predicts that help reduces students' self-confidence and motivation which leads them to exert less effort to persist at the university. This is because the university will only help low-ability. Offering help will thus reveal to the student "bad news" about her probability of success at the university. For students in our setting who have already received negative information about their ability via the probation label, the offer of help will compound any discouragement effects due to probation. An additional assumption of the model is that effort and ability are complements in the production of performance, and so help is predicted to lower both effort and performance. On the other hand, encouragement has the opposite effect. This is because providing encouragement is analogous to revealing to the student "good news" about her probability of success at the university. Encouragement is therefore predicted to boost self-confidence and motivation, which in turn induces students to work harder to persist at the university and translates into improved performance.

The results from our analysis show that probation in combination with coaching improves

students' GPA and does not increase dropout nor lowers graduation rates. These results are consistent with the model's predictions for encouragement, but go in the opposite direction to the predictions of help. This suggests that the program is effective because it provides encouragement.

7 Conclusion

This paper shows that a universal higher education policy—academic probation—has unintended and unequal consequences. We find that while probation leaves high-income students largely unaffected, it substantially increases dropout and lowers graduation rates for low-income students, thereby widening socioeconomic gaps in degree completion. These findings underscore that institutional rules, even when intended as neutral performance standards, can impose hidden costs on already disadvantaged groups and contribute to persistent inequality in higher education.

At the same time, we demonstrate that policy design matters. When probation was paired with a low-cost coaching program, the negative effects on low-income students disappeared and both low- and high-income students saw meaningful gains in GPA. This suggests that relatively modest reforms can shift probation from a discouragement mechanism into a supportive intervention. In the context of declining intergenerational mobility and widening income disparities, our findings underscore that institutional policy design is not neutral: poorly structured policies can exacerbate inequality, while modest adjustments can enhance both equity and efficiency in higher education.

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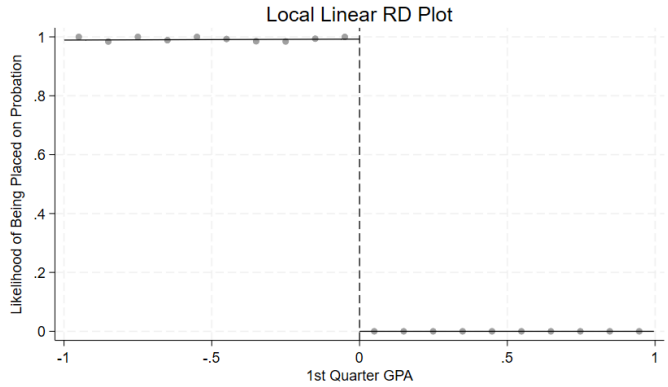
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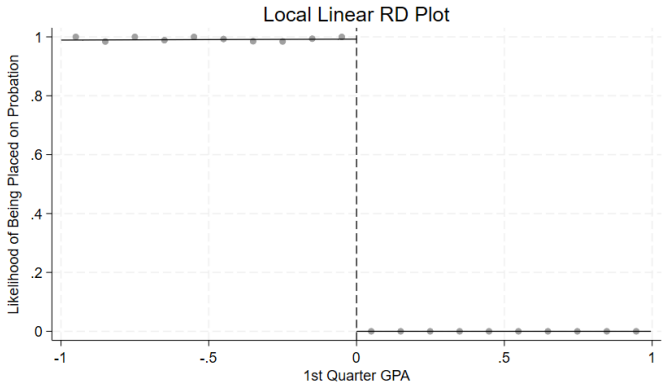
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A Figures

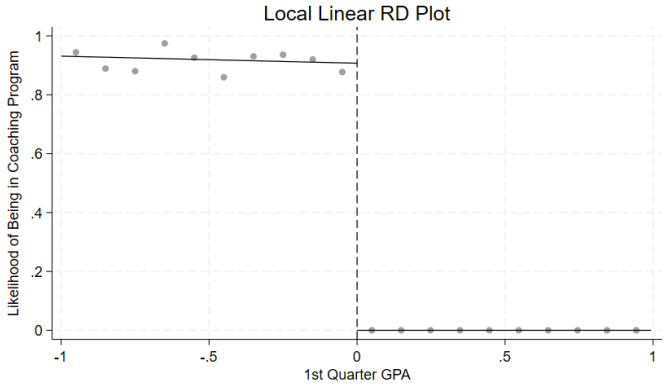
Figure 1: Policies in Practice



(a) Probation likelihood, probation only cohorts



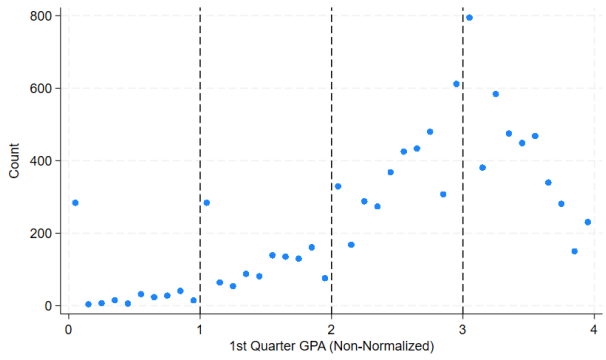
(b) Probation likelihood, probation + SP cohorts



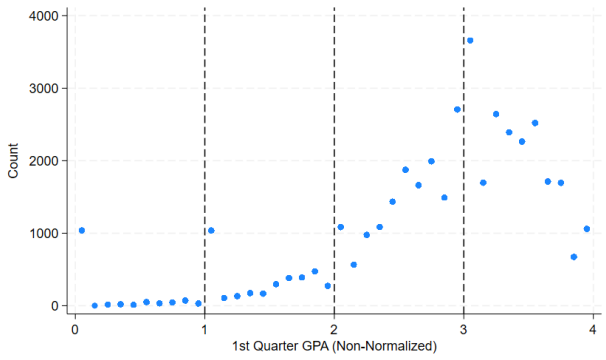
(c) Coaching program placement

Notes: The sample in Figure 1a includes all first-time freshmen entering the university in fall cohorts 2007, 2008 and 2009 (select faculties)—i.e., those exposed to only probation. Figures 1b and 1c include cohorts exposed to both probation and the success program. The sample in Figures 1b and 1c include all first-time freshmen entering the university in the fall cohorts 2010-2017. In all figures, the running variable is first quarter GPA. Circles represent local averages over a 0.1 GPA range. Figures are drawn using a linear fit on either side of the cutoff.

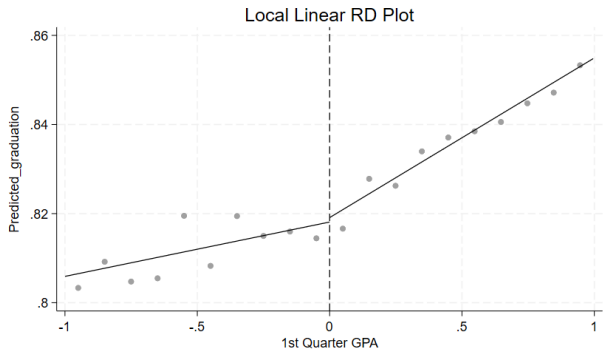
Figure 2: Identification Checks



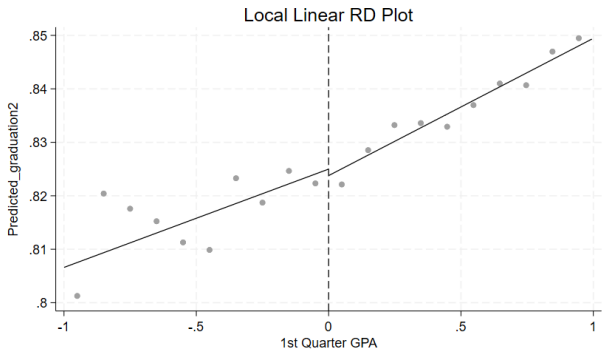
(a) Distribution of Q1 GPA, probation only cohorts



(b) Distribution of Q1 GPA, probation + SP cohorts



(c) Predicted Graduation Rate, probation only cohorts



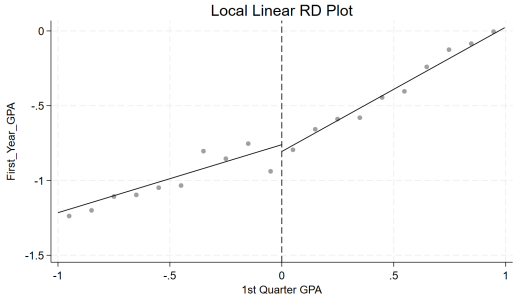
(d) Predicted Graduation Rate, probation + coaching cohorts

Notes: The sample used in Figures 2a and 2c includes cohorts exposed to academic probation only (2007, 2008 and part of 2009 cohort). The sample in Figures 2b and 2d includes all cohorts exposed to both SP and probation (the four colleges of the 2009 cohort and 2010-2017 cohorts). Circles represent local averages over a 0.1 GPA range. The running variable is first quarter GPA. Figures 2c and 2d are drawn using a linear fit on either side of the cutoff. Predicted outcomes are based on the following controls: SAT scores, gender dummy variable, non-white dummy variable, California resident dummy variable, pell eligibility dummy variable, EFC scores, mothers' and fathers' college graduation dummy variables.

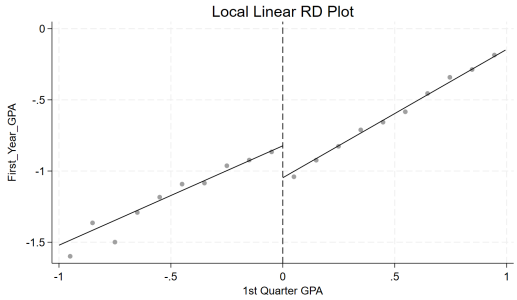
Figure 3: RD Figures for Academic Outcomes

Probation Cohorts

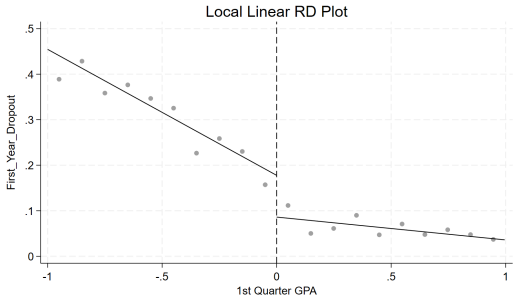
Probation + Coaching Cohorts



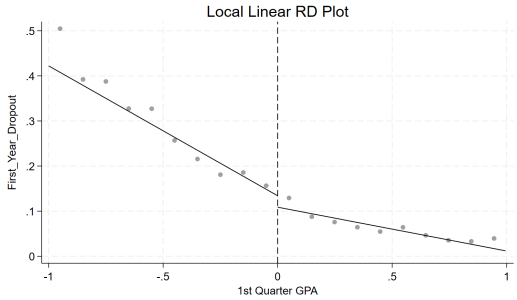
(a) Q2 + Q3 GPA



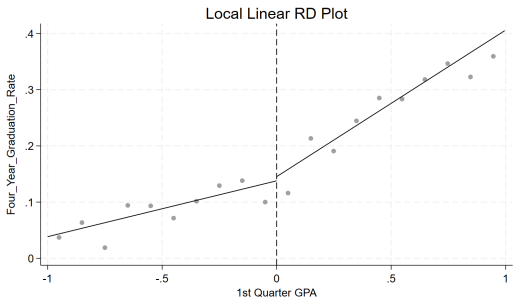
(b) Q2 + Q3 GPA



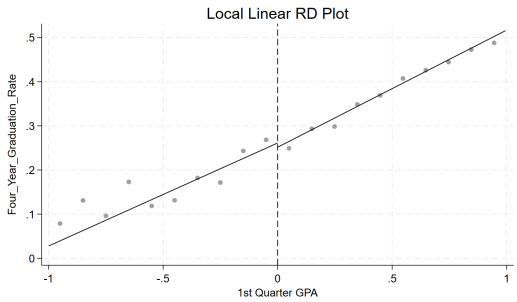
(c) Year 1 Dropout



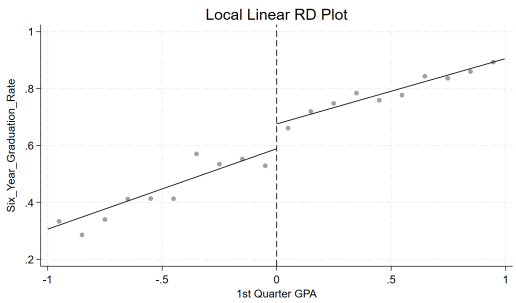
(d) Year 1 Dropout



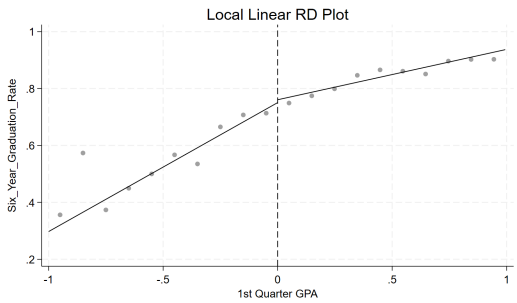
(e) 4-Year Graduation



(f) 4-Year Graduation



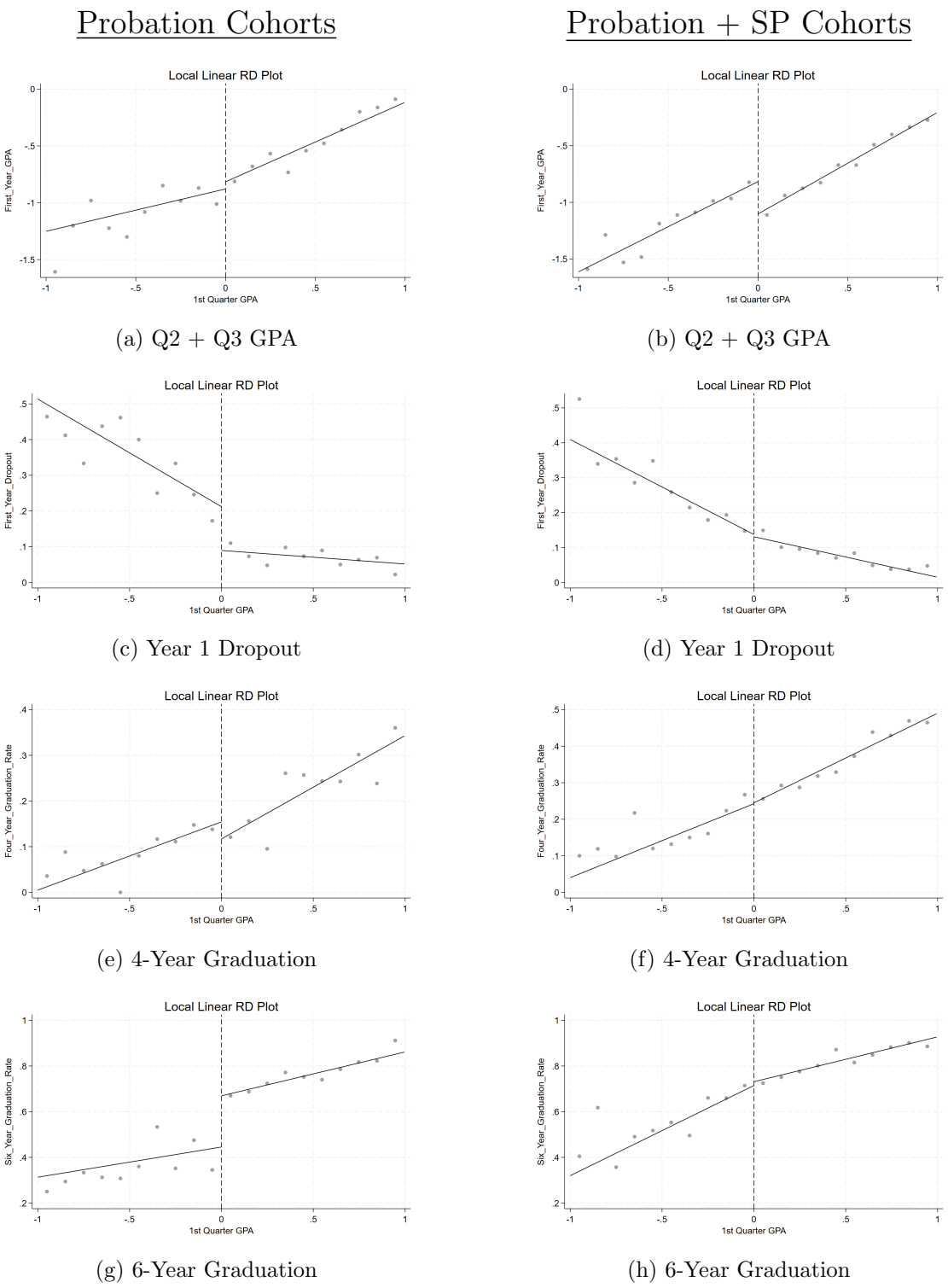
(g) 6-Year Graduation



(h) 6-Year Graduation

Notes: Probation-only cohort figures include the sample of students enrolled at the university in 2007, 2008 and a subset of colleges in 2009. Probation+coaching figures include the sample of students enrolled at the university in select colleges in 2009 and all cohorts from 2010 to 2017 (except for graduation outcomes which include up to the 2014 cohort). Circles represent local averages over a 0.1 GPA range. Figures are drawn using a linear fit on either side of the cutoff.

Figure 4: RD Figures for Academic Outcomes—Low-income Students



(a) Q2 + Q3 GPA

(b) Q2 + Q3 GPA

(c) Year 1 Dropout

(d) Year 1 Dropout

(e) 4-Year Graduation

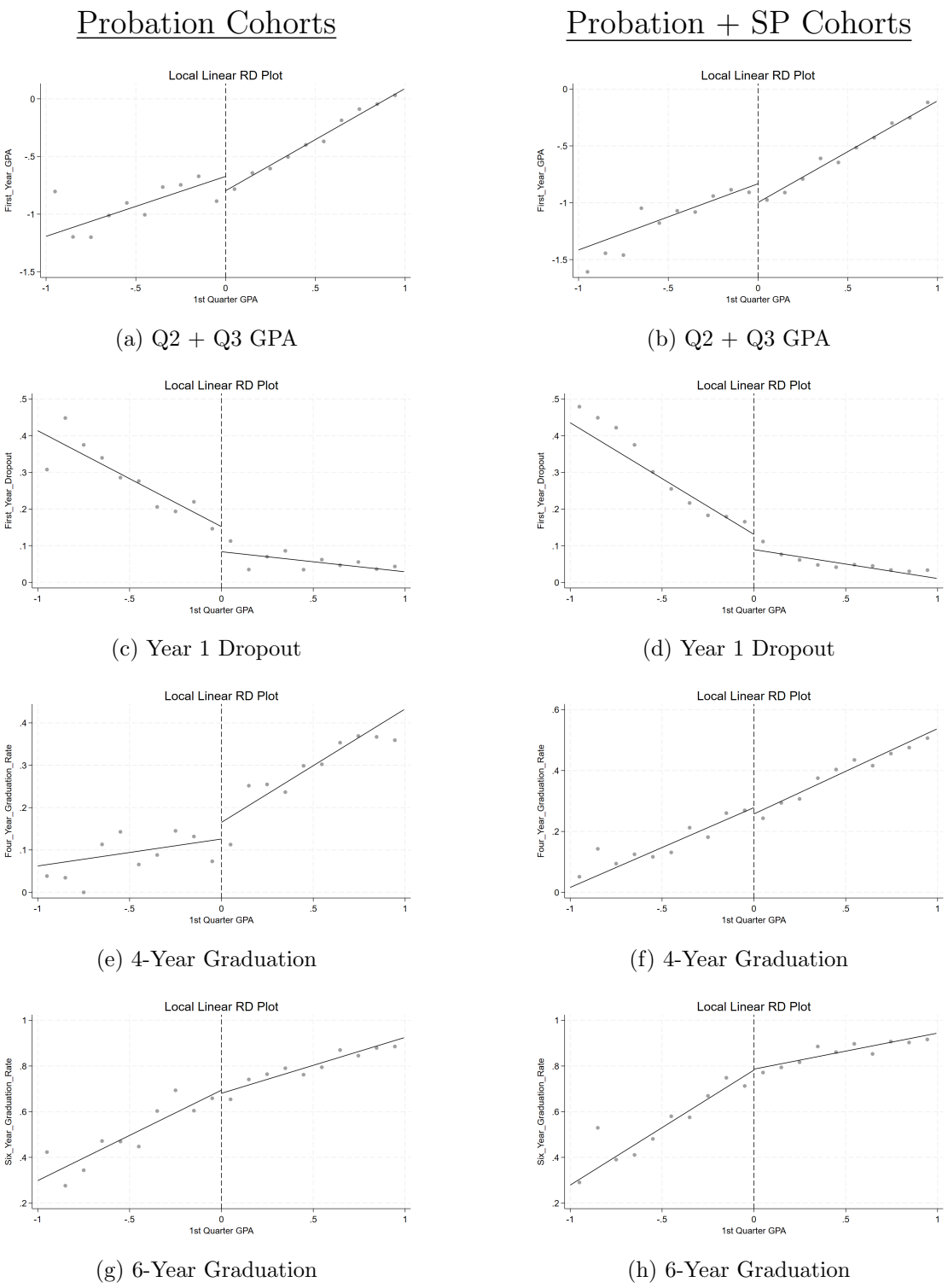
(f) 4-Year Graduation

(g) 6-Year Graduation

(h) 6-Year Graduation

Notes: Sample includes only low-income students, i.e. those with an Expected Family Contribution of less than $30,000. Probation-only cohort figures include the sample of students enrolled at the university in 2007, 2008 and a subset of colleges in 2009. Probation+SP figures include the sample of students enrolled at the university in select colleges in 2009 and all cohorts from 2010 to 2017 (except for graduation outcomes which include up to the 2014 cohort). Circles represent local averages over a 0.1 GPA range. Figures are drawn using a linear fit on either side of the cutoff.

Figure 5: RD Figures for Academic Outcomes—High-income Students



(a) Q2 + Q3 GPA

(b) Q2 + Q3 GPA

(c) Year 1 Dropout

(d) Year 1 Dropout

(e) 4-Year Graduation

(f) 4-Year Graduation

(g) 6-Year Graduation

(h) 6-Year Graduation

Notes: Sample includes only high-income students, i.e. those with an Expected Family Contribution of more than $30,000. Probation-only cohort figures include the sample of students enrolled at the university in 2007, 2008 and a subset of colleges in 2009. Probation+SP figures include the sample of students enrolled at the university in select colleges in 2009 and all cohorts from 2010 to 2017 (except for graduation outcomes which include up to the 2014 cohort). Circles represent local averages over a 0.1 GPA range. Figures aredrawn using a linear fit on either side of the cutoff.

B Tables

Table 1: Summary Statistics

	Probation Only		Probation + Coaching	
	Whole Sample	RD Sample	Whole Sample	RD Sample
	(1)	(2)	(3)	(4)
Demographic and Academic Controls				
SAT Math	628	615	653	636
	(75)	(74)	(72)	(70)
SAT Reading	575	561	596	577
	(75)	(74)	(75)	(74)
Female	0.47	0.43	0.48	0.45
	(0.50)	(0.49)	(0.50)	(0.50)
Non-white	0.33	0.37	0.39	0.44
	(0.47)	(0.48)	(0.49)	(0.50)
Resident	0.94	0.94	0.85	0.86
	(0.25)	(0.24)	(0.35)	(0.34)
Pell Grant Eligible	0.13	0.14	0.17	0.20
	(0.33)	(0.35)	(0.38)	(0.40)
EFC Missing	0.66	0.65	0.57	0.55
	(0.47)	(0.48)	(0.49)	(0.50)
Father Education	0.81	0.79	0.80	0.77
	(0.39)	(0.41)	(0.40)	(0.42)
Mother Education	0.82	0.80	0.83	0.80
	(0.39)	(0.40)	(0.38)	(0.40)
Academic Outcomes				
First-year GPA (Q2+Q3)	2.76	2.46	2.90	2.55
	(0.67)	(0.59)	(0.63)	(0.55)
First-year Dropout	0.09	0.10	0.06	0.08
	(0.29)	(0.30)	(0.23)	(0.27)
4-year Graduation	0.34	0.26	0.47	0.38
	(0.47)	(0.44)	(0.50)	(0.49)
Graduation	0.80	0.74	0.88	0.83
	(0.40)	(0.44)	(0.33)	(0.38)
Treatment Variables				
Probation First Quarter	0.13	0.19	0.07	0.13
	(0.34)	(0.39)	(0.26)	(0.34)
Coaching Participation	0.00	0.00	0.06	0.11
	(0.00)	(0.00)	(0.24)	(0.32)
Observations (Individuals)	8,632	4,595	37,266	17,528

Notes: The sample includes all first-time freshmen with non-missing high school GPA. Means and standard deviations (reported in parentheses). The "Only Probation Policy Existed" sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "Probation + Coaching Policy Existed" sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. The RD sample in columns (2) and (4) represents all students with a GPA between 1 and 3 points.

Table 2: RD Estimates of Probation Policies on Academic Outcomes

	GPA (Q2+Q3)	**Year-1 Dropout**	**4-year Grad.**	**6-year Grad.**
	(1)	(2)	(3)	(4)
Probation Effect	0.002	0.087**	0.039	-0.080
	(0.098)	(0.041)	(0.032)	(0.055)
Observations	1,898	1,879	2,378	1,979
CCT Bandwidth	0.500	0.483	0.588	0.503
Probation + Coaching Effect	0.242***	0.028	0.027	0.015
	(0.061)	(0.026)	(0.031)	(0.037)
Observations	5,708	4,924	4,125	3,291
CCT Bandwidth	0.437	0.369	0.412	0.372
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Selector	CCT	CCT	CCT	CCT

Notes: The "probation sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "probation + Coaching sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. Each point estimate is from a separate RD regression. The CCT bandwidth selector is used to determine the optimal bandwidths for each regression. All local linear RD regressions use a triangular kernel function. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. GPA outcomes are standardized by cohort and reported for all students. Robust standard errors are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 3: RD Estimates of Probation Policies By Socioeconomic Background

	GPA (Q2+Q3)	**Year-1 Dropout**	**4-year Grad.**	**6-year Grad.**
	(1)	(2)	(3)	(4)
Low SES				
Probation Effect	-0.147	0.114*	0.079	-0.228***
	(0.173)	(0.063)	(0.048)	(0.083)
Probation + Coaching Effect	0.308***	0.013	0.027	0.007
	(0.094)	(0.033)	(0.052)	(0.049)
Observations (Prob.)	574	885	725	631
Observations (Prob. + Coach)	2,187	2,863	1,665	1,546
CCT Bandwidth (Prob.)	0.405	0.582	0.484	0.431
CCT Bandwidth (Prob. + Coach)	0.373	0.463	0.339	0.399
High SES				
Probation Effect	0.112	0.070	0.023	0.036
	(0.117)	(0.051)	(0.048)	(0.066)
Probation + Coaching Effect	0.208***	0.045	0.044	-0.007
	(0.078)	(0.039)	(0.040)	(0.059)
Observations (Prob.)	1,262	1,224	1,134	1,287
Observations (Prob. + Coach)	3,594	2,462	2,587	1,427
CCT Bandwidth (Prob.)	0.556	0.512	0.467	0.544
CCT Bandwidth (Prob.+ Coach)	0.511	0.339	0.458	0.330
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Selector	CCT	CCT	CCT	CCT

Notes: The "probation sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "probation + Coaching sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. Low-income students are those with an Expected Family Contribution of less than $30,000 while high-income students are those at or above this threshold. Each point estimate is from a separate RD regression. The CCT bandwidth selector is used to determine the optimal bandwidths for each regression. All local linear RD regressions use a triangular kernel function. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. GPA outcomes are standardized by cohort and reported for all students. Robust standard errors are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Donut RD Estimates of Probation Policies

	GPA (Q2+Q3)	**Year-1 Dropout**	**4-year Grad.**	**6-year Grad.**
	(1)	(2)	(3)	(4)
All Students				
Probation Effect	0.011	0.096**	0.028	-0.067
	(0.105)	(0.044)	(0.038)	(0.058)
Probation + Coaching Effect	0.301***	0.003	0.049	0.034
	(0.070)	(0.029)	(0.034)	(0.039)
Observations (Prob.)	1,852	1,734	1,752	1,852
Observations (Prob. + Coach)	4,576	4,505	3,733	3,114
CCT Bandwidth (Prob.)	0.536	0.481	0.498	0.520
CCT Bandwidth (Prob. + Coach)	0.425	0.375	0.413	0.410
Low SES				
Probation Effect	-0.312	0.144**	0.060	-0.268***
	(0.204)	(0.066)	(0.061)	(0.095)
Probation + Coaching Effect	0.313***	-0.011	0.007	0.000
	(0.104)	(0.036)	(0.052)	(0.055)
Observations (Prob.)	498	754	550	569
Observations (Prob. + Coach)	2,074	2,789	1,617	1,426
CCT Bandwidth (Prob.)	0.392	0.560	0.423	0.431
CCT Bandwidth (Prob. + Coach)	0.401	0.485	0.381	0.420
High SES				
Probation Effect	0.179	0.069	0.000	0.052
	(0.125)	(0.051)	(0.057)	(0.070)
Probation + Coaching Effect	0.299***	0.024	0.083*	0.048
	(0.090)	(0.041)	(0.046)	(0.059)
Observations (Prob.)	1,334	1,205	871	1,235
Observations (Prob. + Coach)	2,901	2,357	2,039	1,581
CCT Bandwidth (Prob.)	0.577	0.544	0.433	0.558
CCT Bandwidth (Prob.+ Coach)	0.462	0.354	0.421	0.367
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Selector	CCT	CCT	CCT	CCT

Notes: The "probation sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "probation + Coaching sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. Low-income students are those with an Expected Family Contribution of less than $30,000 while high-income students are those at or above this threshold. Each point estimate is from a separate 'Donut' RD regression where we exclude the heaping point at the 2.0 GPA cutoff. The CCT bandwidth selector is used to determine the optimal bandwidths for each regression. All local linear RD regressions use a triangular kernel function. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. GPA outcomes are standardized by cohort and reported for all students. Robust standard errors are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

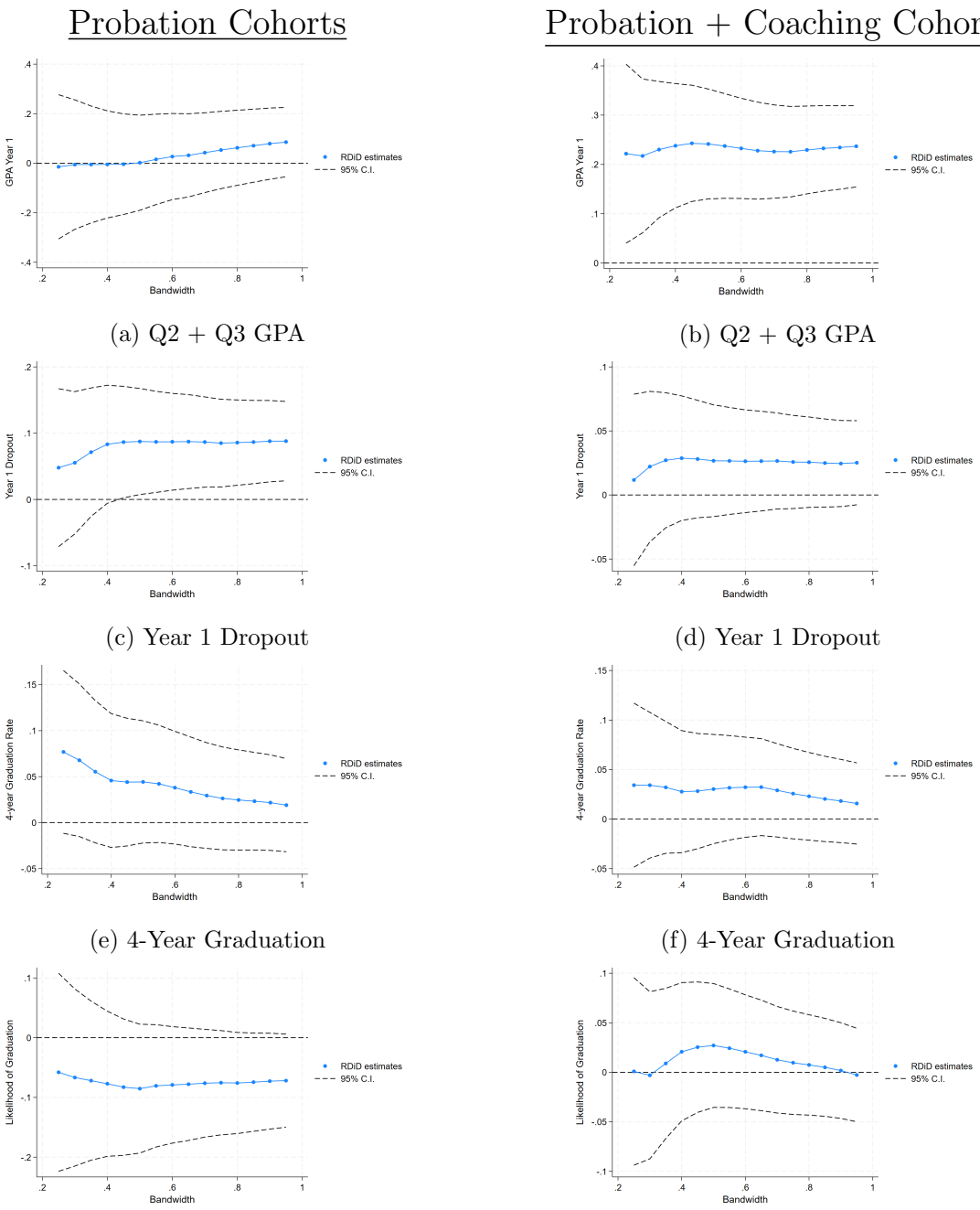
Table 5: Persistence at University by Year for each Policy

	(1) Complete Yr 2 (or Graduate)	(2) Complete Yr 3 (or Graduate)	(3) Complete Yr 4 (or Graduate)	(4) Complete Yr 5 (or Graduate)	(5) Complete Yr 6 (or Graduate)
Probation Only					
All Students	-0.113**	-0.049	-0.063	-0.077	-0.066
	(0.055)	(0.050)	(0.056)	(0.057)	(0.052)
Low-SES	-0.168*	-0.185**	-0.224***	-0.218***	-0.199**
	(0.087)	(0.083)	(0.083)	(0.082)	(0.078)
High-SES	-0.071	0.049	0.056	0.029	0.037
	(0.066)	(0.059)	(0.068)	(0.070)	(0.067)
Observations (All)	1,582	2,379	1,852	1,897	2,361
CCT Bandwidth (All)	0.430	0.590	0.471	0.494	0.584
Observations (Low SES)	609	687	680	632	776
CCT Bandwidth (Low SES)	0.418	0.459	0.441	0.433	0.532
Observations (High SES)	1,042	1,472	1,134	1,217	1,278
CCT Bandwidth (High SES)	0.435	0.580	0.467	0.501	0.533
Probation + Coaching					
All Students	-0.026	0.014	0.047	0.039	0.050
	(0.042)	(0.043)	(0.042)	(0.041)	(0.042)
Low-SES	-0.007	0.017	0.060	0.037	0.053
	(0.055)	(0.059)	(0.061)	(0.063)	(0.061)
High-SES	-0.048	-0.017	-0.010	-0.017	-0.005
	(0.064)	(0.072)	(0.069)	(0.070)	(0.071)
Observations (All)	2,676	2,685	2,826	3,266	2,850
CCT Bandwidth (All)	0.367	0.371	0.407	0.446	0.421
Observations (Low SES)	1,311	1,247	1,247	1,252	1,307
CCT Bandwidth (Low SES)	0.410	0.372	0.372	0.380	0.401
Observations (High SES)	1,116	1,053	1,119	1,164	1,135
CCT Bandwidth (High SES)	0.308	0.278	0.313	0.326	0.322

Notes: The "probation sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "probation + Coaching sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. Low-income students are those with an Expected Family Contribution of less than $30,000 while high-income students are those at or above this threshold. Each point estimate is from a separate RD regression. The CCT bandwidth selector is used to determine the optimal bandwidths for each regression. All local linear RD regressions use a triangular kernel function. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. GPA outcomes are standardized by cohort and reported for all students. Robust standard errors are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

A Appendix Figures

Figure A1: Robustness of Bandwidth Choice for Academic Outcomes



(a) Q2 + Q3 GPA

(b) Q2 + Q3 GPA

(c) Year 1 Dropout

(d) Year 1 Dropout

(e) 4-Year Graduation

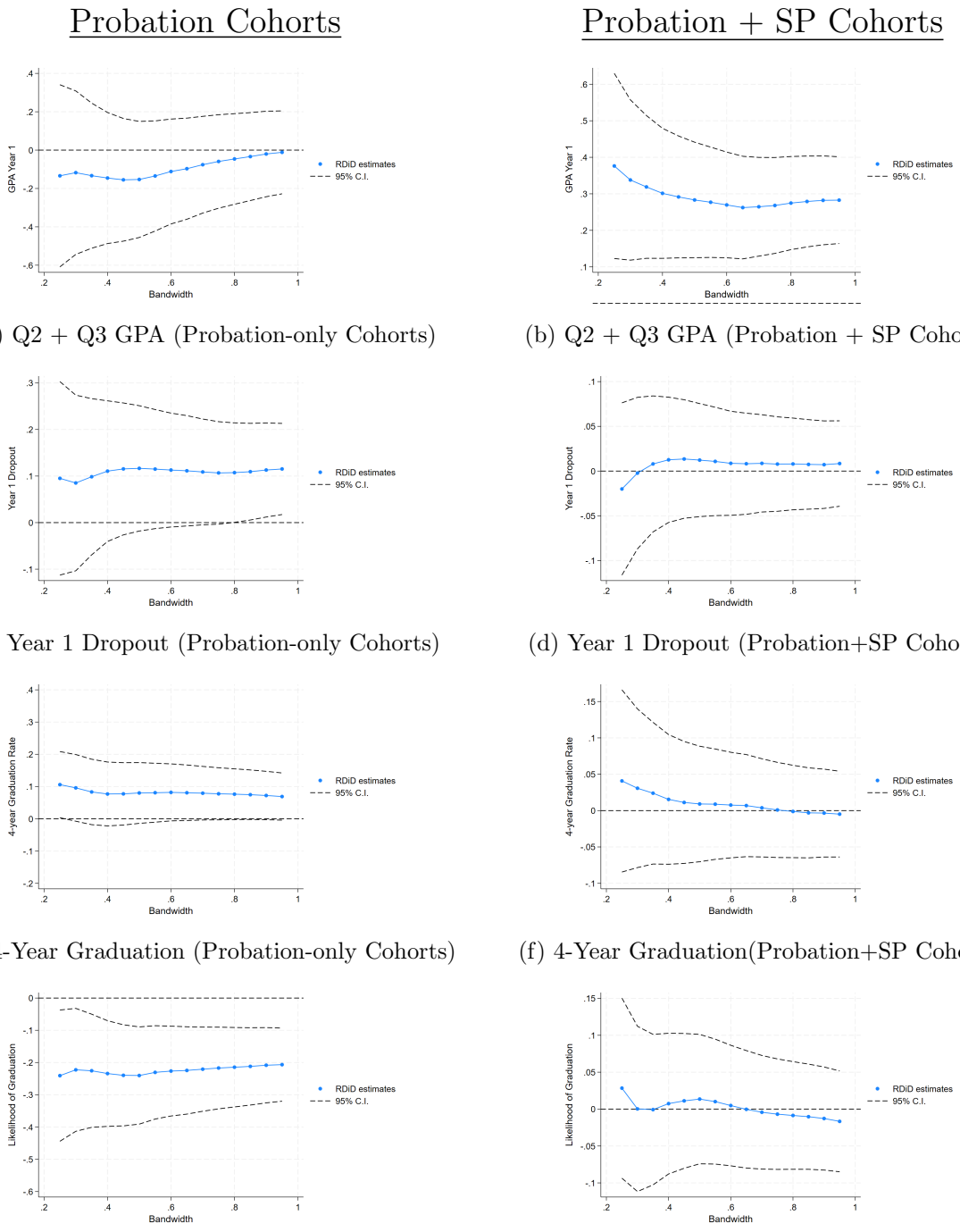
(f) 4-Year Graduation

(g) 6-Year Graduation

(h) 6-Year Graduation

Notes: Probation-only cohort figures include the sample of students enrolled at the university in 2007, 2008 and a subset of colleges in 2009. Probation + coaching figures include the sample of students enrolled at the university in select colleges in 2009 and all cohorts from 2010 to 2017 (except for graduation outcomes which include up to the 2014 cohort). Scatter points represent estimates from local linear regressions ranging from 0.25 to 1 GPA point on either side of the cutoff. Upper and lower 95% confidence intervals are reported using dashed lines. GPA is standardized by cohort and is reported for all students.

Figure A2: Robustness of Bandwidth Choice for Academic Outcomes—Low-Income Students



(a) Q2 + Q3 GPA (Probation-only Cohorts)

(b) Q2 + Q3 GPA (Probation + SP Cohorts)

(c) Year 1 Dropout (Probation-only Cohorts)

(d) Year 1 Dropout (Probation+SP Cohorts)

(e) 4-Year Graduation (Probation-only Cohorts)

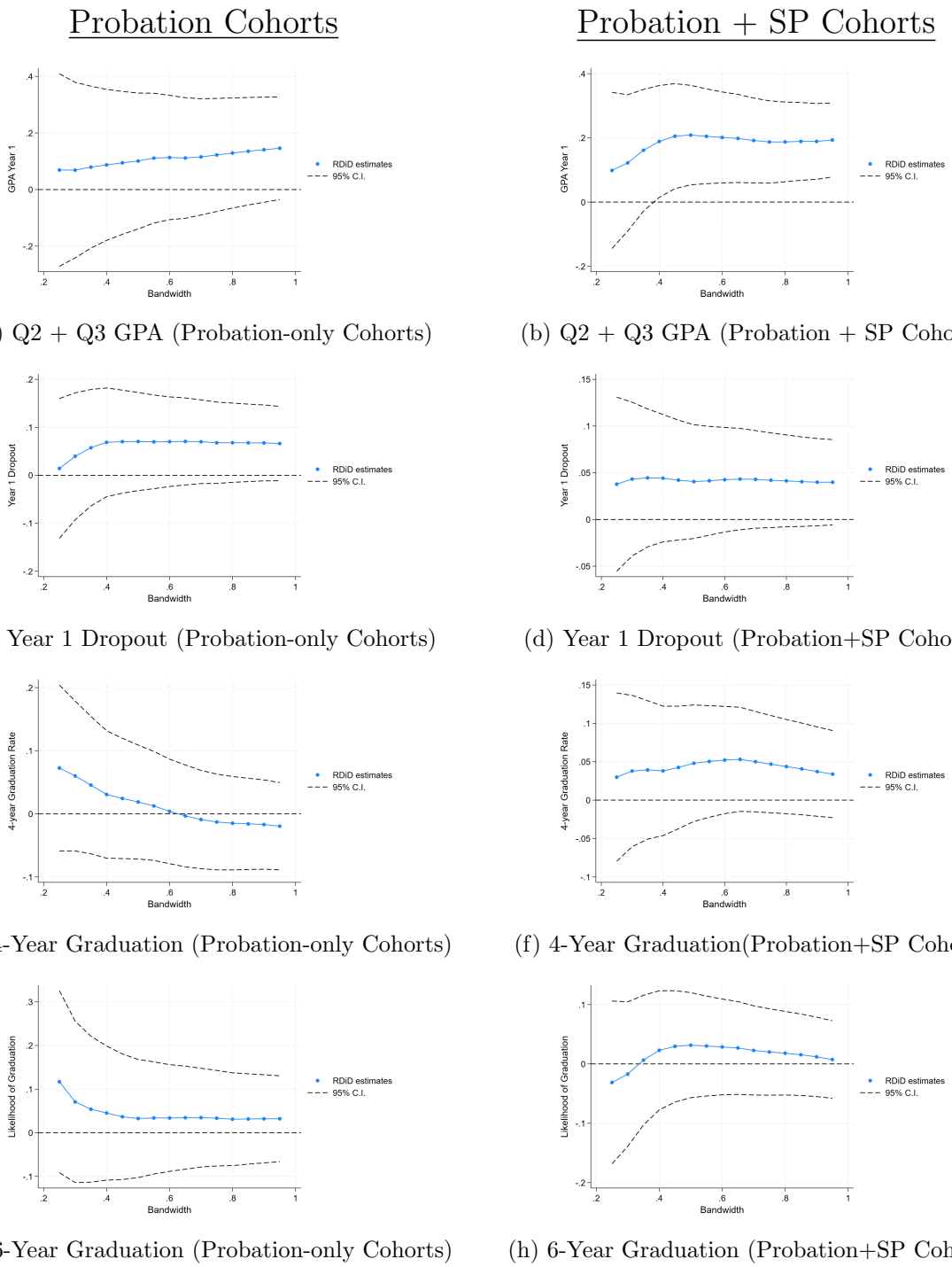
(f) 4-Year Graduation(Probation+SP Cohorts)

(g) 6-Year Graduation (Probation-only Cohorts)

(h) 6-Year Graduation (Probation+SP Cohorts)

Notes: Sample includes only low-income students, i.e. those with an Expected Family Contribution of less than $30,000. Probation-only cohort figures include the sample of students enrolled at the university in 2007, 2008 and a subset of colleges in 2009. Probation+SP figures include the sample of students enrolled at the university in select colleges in 2009 and all cohorts from 2010 to 2017 (except for graduation outcomes which include up to the 2014 cohort). Scatter points represent estimates from local linear regressions ranging from 0.25 to 1 GPA point on either side of the cutoff. Upper and lower 95% confidence intervals are reported using dashed lines. GPA is standardized by cohort and is reported for all students.

Figure 3: Robustness of Bandwidth Choice for Academic and Labor Market Outcomes (High-income)



(a) Q2 + Q3 GPA (Probation-only Cohorts)

(b) Q2 + Q3 GPA (Probation + SP Cohorts)

(c) Year 1 Dropout (Probation-only Cohorts)

(d) Year 1 Dropout (Probation+SP Cohorts)

(e) 4-Year Graduation (Probation-only Cohorts)

(f) 4-Year Graduation(Probation+SP Cohorts)

(g) 6-Year Graduation (Probation-only Cohorts)

(h) 6-Year Graduation (Probation+SP Cohorts)

Notes: Sample includes only high-income students, i.e. those with an Expected Family Contribution of more than $30,000. Probation-only cohort figures include the sample of students enrolled at the university in 2007, 2008 and a subset of colleges in 2009. Probation+SP figures include the sample of students enrolled at the university in select colleges in 2009 and all cohorts from 2010 to 2017 (except for graduation outcomes which include up to the 2014 cohort). Scatter points represent estimates from local linear regressions ranging from 0.25 to 1 GPA point on either side of the cutoff. Upper and lower 95% confidence intervals are reported using dashed lines. GPA is standardized by cohort and is reported for all students.

B Appendix Tables

Table A1: Baseline Covariates Balance Check

	(1) SAT Math	(2) SAT Reading	(3) Female	(4) Non-White	(5) CA Resident	(6) Pell elig.	(7) EFC < $30K	(8) Father college	(9) Mother college
Bandwidth = 0.5									
Probation	11.989*	1.786	-0.044	-0.051	0.036	0.006	0.024	-0.037	-0.008
	(7.146)	(8.420)	(0.046)	(0.056)	(0.028)	(0.045)	(0.056)	(0.050)	(0.049)
Probation + Coaching	4.953	7.371	-0.041	-0.003	0.010	0.001	0.014	0.027	0.030
	(3.858)	(5.145)	(0.029)	(0.031)	(0.021)	(0.026)	(0.031)	(0.027)	(0.026)
Observations (Prob.)	1,891	1,808	1,897	1,898	1,898	1,898	1,898	1,898	1,898
Observations (Prob. + Coaching)	6,398	5,045	6,615	6,615	6,615	6,615	6,615	6,615	6,615
Bandwidth = 0.75									
Probation	9.735	3.780	-0.028	-0.040	0.026	0.018	-0.005	-0.020	-0.000
	(5.977)	(6.872)	(0.039)	(0.045)	(0.021)	(0.036)	(0.045)	(0.040)	(0.039)
Probation + Coaching	5.738	3.385	-0.014	-0.034	0.016	0.018	-0.031	-0.011	0.010
	(5.641)	(6.271)	(0.036)	(0.041)	(0.019)	(0.033)	(0.041)	(0.037)	(0.036)
Observations (Prob.)	3,042	2,882	3,053	3,055	3,055	3,055	3,055	3,055	3,055
Observations (Prob. + Coaching)	3,089	2,926	3,100	3,102	3,102	3,102	3,102	3,102	3,102

Notes: The "probation sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "probation + Coaching sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. Each point estimate is from a separate RD regression. All regressions use either a bandwidth of 0.5 or 0.75 using a triangular kernel. All regressions include cohort and college fixed effects. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Mechanisms: Financial Aid Eligibility and Major Switching

	(1) Year 1 GPA Below 2.0	(2) Switch Major
Probation Only		
All Students	0.036	-0.015
	(0.054)	(0.049)
Low-SES	0.066	0.029
	(0.092)	(0.058)
High-SES	0.016	-0.075
	(0.058)	(0.075)
Observations (All)	1,346	1,584
CCT Bandwidth (All)	0.365	0.430
Observations (Low SES)	552	887
CCT Bandwidth (Low SES)	0.371	0.585
Observations (High SES)	1,013	790
CCT Bandwidth (High SES)	0.442	0.341
Probation + Coaching		
All Students	-0.018	0.013
	(0.026)	(0.023)
Low-SES	-0.071*	0.034
	(0.037)	(0.037)
High-SES	0.030	-0.002
	(0.036)	(0.036)
Observations (All)	4,711	8,143
CCT Bandwidth (All)	0.370	0.573
Observations (Low SES)	2,205	3,230
CCT Bandwidth (Low SES)	0.374	0.506
Observations (High SES)	2,578	3,253
CCT Bandwidth (High SES)	0.388	0.450

Notes: The "probation sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). The "probation + Coaching sample" includes all first-time freshmen enrolled at the university in entering fall cohorts 2009 (select faculties) up until 2017. Low-income students are those with an Expected Family Contribution of less than $30,000 while high-income students are those at or above this threshold. Each point estimate is from a separate RD regression. The CCT bandwidth selector is used to determine the optimal bandwidths for each regression. All local linear RD regressions use a triangular kernel function. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. GPA outcomes are standardized by cohort and reported for all students. Robust standard errors are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

C Theoretical Predictions

We first set up the general model and discuss how it applies to our setting. We classify the different elements of our coaching program into two types of incentive structures: help and encouragement. We then review the predictions of Bénabou and Tirole (2003) regarding how these two incentive structures affect students.

C.1 Model Setup

The model is set up as a game between the university (principal) and the student (agent). A student who scores just below the 2.0 GPA cutoff is on academic probation and faces two choices: she can either decide to improve her academic performance and not drop out from the university, or drop out from the university. In other words, she can choose whether or not to exert effort $e \in \{0; 1\}$ in order to not drop out from the university. The cost of exerting effort or undertaking the task of not dropping out is $c > 0$. The student and university's payoffs are respectively $V > 0$ and $W > 0$ if the student is successful and does not drop out. If the student drops out, both get 0.

Let $\theta \in [0; 1]$ denote the student's probability of success if she decides to exert effort. θ can alternatively be viewed as the student's ability. A key assumption in the model is that the university has more information than the student about her probability of success or ability. Specifically, the university is assumed to perfectly know θ, while the student knows that θ is drawn from a cumulative distribution function $F(\theta)$ with a density $f(\theta)$.

In our setting, both the university and the student know that the student is on academic probation, but the university has more information about the student's probability of success. It can derive this information from having seen the outcomes of other students on academic probation in previous years. For example, the university might think that it is still possible for the student to succeed despite her initial failure, as previous probation students have persisted at the university. On the other hand, it is possible that the university is less trusting of the student or more pessimistic about her chances of success because they have seen previous students be discouraged by academic probation. In both cases, the university is assumed to have superiority of information.

The student may receive a signal $\sigma \in [0; 1]$ about her probability of success θ, with conditional cumulative distribution $G(\sigma|\theta)$ and positive conditional density $g(\sigma|\theta)$. Another key assumption is that the monotone likelihood ratio property (MLRP) holds:

$$\text{for all } \sigma_1 \text{ and } \sigma_2 \text{ with } \sigma_1 > \sigma_2, \ \frac{g(\sigma_1|\theta)}{g(\sigma_2|\theta)} \text{ is increasing in } \theta.$$

Intuitively, the MLRP guarantees that a higher σ is "good news" for the student about her probability of success θ.

The timing of the game is as follows:

Stage 1: The university learns the parameter θ and selects a policy p.[7]

[7] For example, if the university's incentive structure is to offer the student help, the policy p will be the level of help provided.

Stage 2: After observing the policy chosen by the university and learning σ, the student chooses action e.

The student's expected payoff from exerting effort is $\hat{\theta}(\sigma, p)\mathrm{V}$ which can also be viewed as student's intrinsic motivation. Her expected payoff depends on $\hat{\theta}(\sigma, p)$, which is the conditional expectation of her probability of success or her interim self-confidence. The conditioning of $\hat{\theta}$ on p, referred to as the "looking-glass-self", implies that the student tries to see through the university's ulterior motive from choosing p. In other words, the choice of policy may reveal private information that the university has about the student's ability.

Bénabou and Tirole (2003) analyze the perfect Bayesian equilibria of this two–stage game for different types of incentive structures (such as offering rewards, bonuses, help, delegation and encouragement). The intuition behind solving for the equilibrium is as follows:

For a given policy p, the student will only exert effort e if her expected payoff from it is greater than its cost i.e., if $\hat{\theta}(\sigma, p)\mathrm{V} \geq c$. Therefore, there is a cutoff $\sigma^*(p)$ such that the student exerts effort if and only if she receives a signal $\sigma \geq \sigma^*(p)$—which depends on p due to the "looking-glass-self" phenomenon. In other words, $\sigma^*(p)$ is the threshold signal for which the student's expected payoff from exerting effort is equal to its cost, so that any $\sigma \geq \sigma^*(p)$ implies that the expected benefits from effort are higher than its costs.

The university then chooses p to maximize its own expected payoff. The university's choice of p depends on θ and $\sigma^*(p)$. The university might therefore choose to offer different policies to students of different ability levels.[8,9] Observing the university's equilibrium strategy, the student will update her beliefs about $\hat{\theta}$ as well as her expected benefit from exerting effort and subsequently her threshold for exerting effort $\sigma^*(p)$. In other words, the student will infer from the chosen policy information about her true ability, which affects her self-confidence $\hat{\theta}$ and intrinsic motivation (i.e., $\hat{\theta}\mathrm{V}$). This will subsequently determine her optimal action e^* (i.e., whether or not she exerts effort). In most settings, performance is produced by the interaction between effort e and ability θ which are complements. This implies that increasing (lowering) self-confidence should increase (decrease) effort.

The coaching program in our setting includes a bundle of interventions, which can be classified under one of two incentive structures: help and encouragement. Specifically, the program offers students "help" by providing them with information about probation and campus resources, having coaches assist them with time management and goal-setting exercises, and requiring them to meet once individually with their coach or use a campus resource. The other key component of the program is to show students that failure is normal and that it is still possible to succeed despite failure. In what follows, we argue that the university's incentive structure in this case is encouragement

[8] Formally, this follows from the university's maximization problem, the MLRP and additional assumptions that can be imposed depending on the type of incentive structure. For example, as discussed below, when the university is deciding on the level of help to offer students, an additional sorting condition will be imposed. Along with the MLRP, this will make it such that the university offers more help to lower-ability students.

[9] Another assumption is that the university is uncertain about how the student will respond to their choice of policy or how it will affect his intrinsic motivation. Otherwise, they can perfectly predict the student's response to any chosen policy.

or disclosing to the student "good news" about her probability of success. Following Bénabou and Tirole (2003), we reframe the model and derive its predictions under these two incentive structures.

C.2 Help

Assume that the university wants to provide the student with a level of help h (at a private cost h) in case the student decides to exert effort to remain at the university. The probability of success is now defined as the function $P(\theta, h)$, which is increasing in h and θ i.e., $P_h > 0$ and $P_\theta > 0$. As discussed earlier, the student only exerts effort if and only if she receives a signal $\sigma \geq \sigma^*(h)$ where $E[P(\theta, h)|\sigma^*(h), h]V = c$, with $\sigma^*(h)$ being a decreasing function. The university's payoff is $U_P = [1 - G(\sigma^*(h)|\theta)][P(\theta, h)W - h]$.[10]

In the case of help, Bénabou and Tirole (2003) impose a sorting condition:

$$\frac{\partial^2 ln(P(\theta,h)W-h)}{\partial\theta\partial h} < 0$$

The sorting condition means that the percentage increase in the university's payoff due to a higher level of help is lower when the student's ability or probability of success is higher. Bénabou and Tirole (2000) argue that this sorting condition is suitable when we have a zero-one task such as not dropping out of the university. This is because the university's payoff would be independent of the student's margin of success.[11]

In equilibrium, one can show that the university's optimal policy is to offer a higher level of help for students with lower probability of success.[12] Because the university helps less when it is more trusting of the student, a higher level of help is perceived by the student to be "bad news" about her probability of success. This lowers her self-confidence $\hat{\theta}$ and intrinsic motivation $\hat{\theta}V$, which in turn increases $\sigma^*(h)$. This higher threshold effectively decreases the likelihood of exerting effort to not drop out from the university. In summary, help lowers student's self-confidence, motivation and effort, as the offer of help reveals to her that she is low-ability.

C.3 Encouragement

A key element of the coaching program is to communicate to students on probation that they are not the only ones struggling academically, failure is normal and it is still possible to succeed despite probation. Initially, students only see the probation label and as a result, they may think that their probability of success is low. The university however knows that it is still possible to succeed despite probation. In other words, the university has private positive information about student's probability of success. Under the Bénabou and Tirole (2003) model, the university's policy p here is whether or not to disclose to the student this private information (i.e., whether

[10] $[1 - G(\sigma^*(h)|\theta)]$ is the probability that the student exerts effort.

[11] A reversal of the sorting condition would occur in cases where the principal's payoff increases with the margin of success and as a result with the agent's ability. For example, if a professor is coauthoring papers with students, she would be more tempted to help high-ability students as her payoff depends on the margin of success (i.e., the paper's publication outcome).

[12] This follows from the sorting condition and the MLRP.

or not to provide students with encouragement). Importantly, the information to be disclosed by the university is "hard" meaning that students are presented with *evidence* supporting the claim that they can still succeed despite failure.[13] Indeed, the program offers students three pieces of evidence. First, at the beginning of the workshop, students watch a video of various high profile individuals who have succeeded despite previously failing. Second, during the breakout sessions, coaches share their own experience with failure. Third, conducting the workshop in a group setting also provides students with evidence that they are not the only ones on probation.

To understand the implications of encouragement, we look to the model in Section C.1. Recall that the university's policy is whether or not to disclose positive private information about student's probability of success θ. It can be shown that because this private information is "good news" about the student's probability of success, the university's optimal policy would be to disclose the information or provide encouragement.[14] Formally, the university's policy here would be to release a signal that covaries positively with θ. Because the student is receiving a positive signal about her probability of success, her self-confidence and intrinsic motivation increase. The boost in self-confidence will in turn increase the likelihood of exerting effort towards persisting at the university.

To summarize, this model predicts that in our context, disclosing "good" news with hard evidence about the student's probability of succeeding (or encouragement with evidence) increases her motivation and self-confidence. This in turn pushes the student to work harder towards the goal of persisting at the university. On the other hand, offering a student help lowers her self-confidence and motivation, which induces her to work less. The coaching program we focus on offers both help and disclosure of information. As a result, it is unclear whether, ex-ante, the program is expected to improve student performance and persistence.

[13] This is important because if the information is "soft" (for example, encouragement or praise without evidence), the student will see through the university's ulterior motive of simply wanting to boost her self-confidence and may not believe the information (i.e., cheap talk).

[14] Conversely, the university would want to conceal "bad news" about the student's probability of success.

D SP Workshop Materials

Campus Resource Guide

Campus Resources (Scan QR codes to learn more!)

1-3: Study Skills: Find resources and videos on popular topics such as:

- Study strategies, text anxiety tips and study guides
- Flashcards, video tutorials, interactive exercises
- Lecture note taking
- Memorization
- Learning style (Vark Questionnaire)

Study Skills

4-5: Tutoring on Campus (Location Varies)

- Free 1-1 or group tutoring for a variety of classes
- Supplemental Workshops: 1 unit workshop to go alongside certain Science and Math classes. Recap information from class, get help with study skills, test prep, and group studying.
- Study sessions: Weekly sessions made of 8-15 students for multiple subjects. Submit a request through the portal

Tutoring

6-7: Office hours can sometimes be intimidating and confusing on what you should ask. Here are some helpful tips:

- If office hours conflict with your schedule, contact professors for an alternate time to meet. They are more than happy to help out!
- Show problems on homework or tests that you were confused about, ask the professor to walk you through each steps.
- Bring in class notes that you would like more explanations on
- Explain your study strategies and ask about additional tips or tricks

Professors are very knowledgeable in their field and know of many outside resources and sometimes even internship or research opportunities, get to know them!

8-9: Associated Students, Inc. (ASI):

- Student Government
- Clubs and Organization
- Craft Center Classes
- The Recreation Center
- Activities and events

ASI

Dean of Students

- Club Sports
- Center For Service in Action
- Center for Leadership
- Fraternity & Sorority Life

Dean of Students

10: Cross Cultural Centers(Location varies)

- **Gender Equity Center-** Educating and empowering feminist, womxnist, mujerista moments though an intersectional lens and striving for social justice.
- **Men & Masculinity-** Creates spaces to express and evaluate masculinity and intersections with other identities through programs, dialogs and trainings.
- **Multicultural Center-** Provides space and events for people across all races, ethnicities, gender, sexual orientation, disability, economic class, religion, citizenship and their intersections
- **Pride Center-** Provides brave spaces and events to all sexualities, gender identities and expressions. Check out their peer mentoring program!

CCCs

Student Academic Services (Location Varies)

- **Dream Center-** Offers an inclusive space and a multitude of events for all undocumented students, those in mixed-status families and their allies. Stop by for a space to study, or to hang out with friends!
- **Black Academic Excellence Center (BAEC)-** Offers a supportive and enriching environment to promote excellence among Black students on campus. Stop by their center to say hello or attend one of their events!

SAS

11-14: Campus Health and Wellbeing (Bldg. 27):

Health Services:

- Mostly free services
- Walk in or make an appointment for medical attention or advice
- Educational programs about drugs, alcohol, sexuality and other topics
- On site lab testing, X-rays, and Shots (e.g Flu, TB tests)
- Discounted Pharmacy
- After-hours nurse advice
- PULSE peer mentoring health education program, covering topics such as, drugs and alcohol use and/or recovery, physical and sexual health and mental well being.

Health & Wellbeing

Counseling Services:

- Individual, couples, group therapy sessions
- Emotional Well Being Workshops
- End of Quarter Survival Kit Workshops
- Clinicians specializing in: Anxiety, Eating Disorders, Multicultural issues, Trauma, Alcohol and Drug Abuse, Suicide Prevention and many more.

Counseling Services

15-18: Basic Needs & Crisis Services (Location Varies)

Food Insecurity:

- CalFresh- Provides monthly payments to eligible students that can be used where food is sold like grocery stores, and farmers markets.
- Meal Vouchers- Students experiencing short-term financial need, can dine at 805 Kitchen during the school year and The Avenue for the summer.
- Food Pantry (Bldg 27, Lower Level)- Students can access free, packed and canned foods, frozen meals and personal hygiene products.
- Food Bank Distribution- Once a week on Mott Lawn, bags of fresh produce and food for free.

Basic Needs

Financial Hardships:

- Cares Grant- One-time grant for unexpected emergencies like, paying for tuition, academic supplies, medical expenses, emergency housing and other temporary hardships.
- Professional Clothing Closet- Free, high-quality work clothes for interviews and future internships and jobs
- Financial Aid Office: Offers daily drop in hours where students can meet with a counselor to discuss ways to cover the cost of college.

15-18 (Cont.): Crisis Services

- Safer (Bldg 65, Rm 217)- Provides confidential crisis counseling, advocacy and education and support resources by state-certified advocates. Learn about your options, rights, and other resources about sexual assault or misconduct, dating or domestic violence and stalking.

Safer

Reporting Hate Crimes

- Bias Incident Report- If you believe you have witnessed an act of discrimination or harassment on or off campus, you may file a report online though the Dean of Students.

Bias Incident Report

19-20: Career Services (Bldg. 124): Drop in or make an appointment with the Freshman Focus Team or any other Career Counselor to talk about:

- Career exploration
- Major Exploration
- Interviewing skills
- Resume and Cover letter

Career Services

21-22: Advising Centers: Have a question and don't know where to start? Visit an advisor!

College Advising Center: CAED, CAFES, CENG, CLA, CSM, OCOB,

- Course planning
- Navigating your curriculum
- Major and support related classes
- Tracking progress to degree
- Concentration

Specialty Advising

- Pre-Health Career Advising
- International/Study Abroad

Success Center (Bldg 52-D37):

- Referring you to academic and/or on-campus resources
- Understanding university and college-specific policies and procedures
- Navigating tools such as PASS and Student Center
- Change of Major process
- GE Classes
- Minors
- Transfer courses

Advising

23-24: Conflict resolution Ombuds (Library 35-113):

- If you feel that you got an unfair grade in a class
- If you feel that you got treated unfairly by someone in the University Community
- If you want to discuss a sensitive question or issue

Ombuds

25: Disability Resource Center (Bldg. 124): Provides services to those with long-term <u>or</u> short-term disabilities:

- How to request services
- Eligibility
- Information on testing for Learning Disabilities
- Possible accommodations - in and outside the classroom
- Peer Mentor Program

DRC

xx

My Success Plan

I decided to attend University X because:

_____
_____

A positive experience I have had at University X:

_____
_____

My favorite part of University X:

_____
_____

During my time at University X, I am most looking forward to:

_____
_____

Creating S.M.A.R.T. Goals

S	M	A	R	T
Specific Make your goal detailed and specific to know what you are working towards	**Measurable** Set parameters so that you can identify tangible evidence towards achieving your goal	**Attainable** Draft realistic goals that challenge you but you are confident to achieve	**Relevant** Make sure each goal is consistent with other goals you have established and fits with your immediate and long-term plans	**Time-Bound** Set a time that you would like to achieve your goal by

Original Goal:		**SMART Goal:**
I want to read more	**S**: 12 books a year **M**: 1 book a month **A**: 1 hour at lunch, 1 hour before bed **R**: More than currently reading **T**: 1 book a month, 12 a year	I am going to read 1 book a month by reading for an hour during lunch and an hour before bed for a total of 12 books a year.

ACADEMIC SKILLS CENTER

Weekly Schedule

	Sun	Mon	Tues	Wed	Thurs	Fri	Sat
6:00 AM							
7:00 AM							
8:00 AM							
9:00 AM							
10:00 AM							
11:00 AM							
12:00 PM							
1:00 PM							
2:00 PM							
3:00 PM							
4:00 PM							
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6:00 PM							
7:00 PM							
8:00 PM							
9:00 PM							
10:00 PM							
11:00 PM							
12:00 PM							
1:00 AM							
2:00 AM							

Quarter Schedule

	Sun	Mon	Tues	Wed	Thurs	Fri	Sat
Week 1							
Week 2							
Week 3							
Week 4							
Week 5							
Week 6							
Week 7							
Week 8							
Week 9							
Week 10							
Week 11							
Finals							