The Disparate Long-run 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 probation in widening socioeconomic gaps in educational attainment and earnings. We use a regression discontinuity design, leveraging as-good-as-random variation in probation placement at a large California public university. Results indicate that low-income students experience significant decreases in graduation rates and income at the ages of 28 to 33, while high-income students remain unaffected. These findings highlight the potential for academic probation to exacerbate existing inequalities.

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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, Goodman, and Hurwitz, 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., 2023). 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 examines the role of an important higher education policy, academic probation, in exacerbating socioeconomic disparities in college completion and post-graduation earnings. Academic probation 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.

Academic probation serves as a label or warning to students who fail to meet minimum grade point average (GPA) requirements. While the policy is well-intentioned, as it is meant to motivate students to improve their performance, it has been shown to have short-run discouragement effects for some populations (Lindo, Sanders and Oreopoulous, 2010). If these discouragement effects persist in the labor market and disproportionately impact low-income students, such a policy will hinder upward mobility and exacerbate income inequality. However, no previous work has examined whether probation widens socioeconomic gaps in academic or labor market outcomes. In this paper, we aim to fill this important gap in the literature.

Our analysis uses data from a large and selective public four-year university in California, where students are placed on academic probation if their first-quarter GPA is below a 2.0. To estimate the causal effect of probation, we use a regression discontinuity design 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 collect administrative data on students who first enrolled at this university from the years 2007 to 2009. Our data allow us to observe students in each quarter they are enrolled at this university and thus, allow us to estimate how probation affects their academic performance, persistence, and likelihood of graduation. We then match the student academic files to administrative data from the California Employment Development Department, which enable us to observe labor market outcomes for all employment covered by California's Unemployment Insurance (UI) program. These data are for the years 2000 to 2022, allowing us to examine the impact of probation on earnings and employment up to roughly age 33.

Our findings indicate that being placed on academic probation significantly reduces graduation rates and earnings, specifically for low-income students. For the full sample, probation has negative effects on 6-year graduation and earnings but estimates are not statistically significant at conventional levels. High-income students' academic and labor market outcomes are largely unaffected by probation. However, low-income students experience a significant 21.7 percentage point (33%) decrease in 6-year graduation rates and a 38% drop in earnings. Taken together, our results indicate that probation exacerbates socioeconomic gaps in higher education attainment and in the labor market.

Our paper relates to an extensive literature which examines how university-level factors determine college students' success. Much of the previous work has looked at institutional factors that have the potential to improve degree completion rates such as per-student spending or resources, financial aid or student loan availability and the provision of academic supports (Bound et al., 2010; Deming and Walters, 2017; Dynarski et al., 2023; Black et al, 2023; Canaan et al., 2024; Chu and Cuffe, 2024). In contrast, relatively few studies have focused on identifying institutional-level policies that may unintentionally hinder degree completion.

Our work is most closely related to studies that have focused on understanding which institutional-level factors or policies may exacerbate low degree completion rates. Ost, Pan and Webber (2018) find that Ohio universities' policy of dismissing low-performing students, who fail to improve their GPA after being placed on probation, reduces their BA completion rates and earnings 8 years after dismissal. Bleemer and Mehta (2024) find that GPA-based major restriction policies decrease average underrepresented minority students' enrollment shares by 20 percent without generating observable efficiency gains. Several previous studies have looked at how academic probation directly affects academic outcomes, but findings are mixed. In their seminal work, Lindo, Sanders and Oreopoulous (2010) show that among Canadian college students, probation increases first-year dropout rates and reduces degree attainment. These effects are concentrated among high-ability students, men and native English speakers. In the U.S. context, 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 the state of Texas.

Our paper is the first to document that academic probation placement substantially widens socioeconomic gaps in college degree completion and earnings. Indeed, no prior work examines how probation or dismissal policies affect low-income students, either in terms of academic or labor market outcomes.[1] Notably, previous studies on probation focus exclusively on academic outcomes and do not track students in the labor market. Our findings highlight that the initial negative academic impacts of probation do not fade out over time. Instead, the probation label results in substantial and persistent losses in earnings through age 33 exclusively driven by low-income students, thus exacerbating socioeconomic inequality.

Finally, our results are further in line with recent evidence on the labor market returns to college. Previous studies find that enrolling as well as persisting in four-year colleges largely boosts students' earnings in their mid- to late 20s, with particularly large effects for those from low-income backgrounds (Hoekstra, 2009; Hastings, Neilson, and Zimmerman 2013; Zimmerman, 2014; Canaan and Mouganie, 2018; Smith, Goodman and Hurwitz, 2020; Black, Denning and Rothstein, 2023; Mountjoy, 2024). We complement this literature by showing that low-income students miss out on the substantial college wage premium associated with this selective university as a result of academic probation.

2 Academic Probation at the University

Our setting is a large, selective, public 4-year university on the central coast of California. The university serves approximately 21,000 students per year and largely focuses on undergraduate education, with a particular emphasis on engineering and agricultural fields. The university is quite selective with an undergraduate acceptance rate of roughly 28%. Additionally, tuition is about $10,000 for residents of the state of California and $25,000 for all other students. Students also tend to be well-prepared academically with the average student in the 2019 entering cohort scoring 1,375 on the SAT exam (top 20% nationally) and 29 on the ACT.

1. Casey et al. (2018) look at whether probation differentially affects minority and non-minority students. They find that probation has no effect on subsequent term dropout rates and improves GPA for both groups, but effects are larger for non-minority students. This is because non-minority students engage in strategic course-taking due to the probation label.

Student retention and academic mismatch are common concerns for universities globally, including this institution. To address these, an academic probation system identifies marginal students and supports their progress. Similar to policies across North America, this system is GPA-based: students with a cumulative or term GPA below 2.0 are placed on probation and notified via institutional letter. They remain on probation until their GPA exceeds 2.0. First-year students are granted a one-year probationary period to improve their GPA and avoid dismissal.

While this policy is meant to serve as a well-intended wake-up call for students falling behind, 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). Empirically, the discouragement effect of academic probation has been documented in previous work by Lindo et al. (2010) and begs the natural question: Who exactly is bearing the brunt of the unintended consequence of this widely applied policy?

3 Data and Summary Statistics

This study relies on administrative data from various sources. First, we utilize administrative student records from the university's Office of Institutional Research. This enables us to track students' trajectories while at university. Second, we link students' records to administrative earnings data taken from the California Employment Development Department. The latter dataset involves the combination of two separate data sources used to administer the state Unemployment Insurance (UI) program: quarterly earnings records and the Quarterly Census of Employment and Wages (QCEW). This enables us to observe students' trajectories in the labor market. The quarterly earnings records include total earnings in the relevant quarter for each employer–employee (firm) pair. The QCEW data contain earnings and employment data at the establishment-quarter level, which we aggregate to the firm level before linking to the earnings data. Both datasets include the universe of individuals who are covered by the UI program in the state of California for the years 2000 to 2022.[2]

Our main analysis focuses on students who entered university in the years 2007, 2008 and 2009. We exclude all cohorts of students enrolled after 2009 because another confounding policy was introduced and 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 confounding policy as

2. We will not observe labor market outcomes for the small share of students who work outside the state of California, are self-employed, or who work for the Federal government. The Employment Development Department has estimated that 92% of employed Californians are included in the data (Gurantz, 2022).

part of a pilot program.[3] Our final sample contains 8,632 first-time, full-time enrolling students. Column (1) of Table 1 contains summary statistics for students' demographic, academic and labor market outcomes. Column (2) focuses on these same outcomes for the sample of 4,595 students with a 1.0 to 3.0 GPA at the end of the first quarter at university, i.e. the marginal sample.

The mean demographic, academic, and potential outcomes of students in our sample reveal some notable differences between the full and marginal groups. Students who enrolled at university between 2007 and 2009 scored an average of 1,190 on the SAT, while marginal students scored 1,163. Female and non-white representation is higher in the full sample (47% and 33%, respectively) than in the marginal group (42% and 37%). Marginal students are more likely to require remedial Math (5%) and English (13%) courses and slightly more likely to qualify for Pell Grants (15%) or federal loan assistance due to lower family contributions, i.e., earned family contribution (EFC) of less than $30,000. Although 80% of students in the full sample have educated parents, this proportion is slightly lower among marginal students.

Finally, Table 1 also summarizes mean potential outcomes of students in our sample. Notably, while 9 percent of students in the full sample are likely to drop out at the end of the first year, those in the marginal sample are 2 percentage points more likely to do so. We also find meaningful long-run differences as 80 percent of students in the full sample end up graduating (within 6 years), while only 73 percent of students in the marginal group do so. In our main analysis, we focus on labor market outcomes at ages 28 to 33. The lower bound is age 28 because early lifetime earnings are known to be noisy and volatile (Hoesktra, 2009). The upper bound of this age range (age 33) is determined by the fact that the oldest cohort in our sample entered university in 2007 and we only observe earnings through the fourth quarter of 2022. Using these data, we find that, for the full sample, 67% of quarters have students employed in the local labor market between the ages of 28 to 33. This number is slightly larger (69 percent) for marginal students. Mean quarterly earnings are $18,083 and $17,685 for the overall and marginal sample, respectively.

4 Identification Strategy

4.1 Regression Discontinuity Design

We use a regression discontinuity design (Lee and Lemieux, 2010; Imbens and Lemieux, 2008) to estimate the causal impact of academic probation on students' academic and labor market outcomes. To do so, we leverage as-good-as-random variation in the likelihood that students are placed on academic probation at the university. Specifically, stu-

3. 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.

dents who score below a 2.0 GPA at the end of their first quarter are placed on probation, while students scoring at or above this cutoff are exempt. Importantly, this policy was fully binding in practice as indicated by the visual evidence reported in Figure 1a, i.e. our "first stage" RD regression. This lends itself to a simple Sharp RD design that compares outcomes of students scoring just below the 2.0 probation cutoff (treated group) to those scoring just above (control group) during their first quarter at university. 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 and control groups to be the causal effect of being placed on academic probation. 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 academic or labor market outcomes for student i in cohort c. D_{ic} is a dummy variable indicating whether student i is below the academic probation 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 being placed on academic probation.

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, Cattaneo and Titiunik, 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 cases where we stack quarterly labor market outcomes for the same individual, we report clustered standard errors at the individual level.

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 grades—just around the 2.0 GPA cutoff—in a way that would cause unobserved determinants of outcome to vary compared to the rest of the students around the cutoff. For example, if more motivated students were able to precisely control their grades around the cutoff compared to less motivated students, then this could potentially bias our estimates. 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 a series of empirical checks and exercises 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 first quarter GPA at the cutoff point (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, and as outlined in Zimmerman (2014); Canaan & Mouganie (2018); Ost, Pan & Webber (2018), 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.

Figure 1b shows the first quarter GPA distribution for all students in our data. This distribution mirrors those found in the aforementioned studies with heaps in the GPA distribution. Notably, in addition to the heap at the probation cutoff of 2.0, 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 figure. 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". This suggests that the most likely cause of these distributional discontinuities is due to the fact that the number of combinations that result in whole-number GPAs are larger than those for decimal GPAs, especially as measured after only one quarter. This is consistent with findings in Zimmerman (2014) and Ost, Pan & Webber (2018).

To further understand whether the observed pattern of grade distributions could be the result of strategic sorting, we test for potential imbalances in student predetermined characteristics. We consider several covariates that are known to be good predictors of future outcomes: SAT scores, gender, race, remedial math requirement, remedial English requirement, Pell grant eligibility, financial aid eligibility and whether a student's father or mother went to college. We summarize results from this exercise in Figures 1c and 1d. These figures take the same form as those after, in that scatter points represent local averages of the outcome over a 0.1 GPA and are reported using a bandwidth of 1 GPA point on either side of the cutoff. The running variable is defined as the number of GPA points above or below the probation threshold. Figures 1c and 1d show that predicted first-year GPA and graduation, as a function of the above controls, are both smooth at the threshold indicating that baseline covariates are balanced at the threshold. We present more formal regression-based evidence using each of the aforementioned baseline characteristics as a separate outcome in Appendix Table A1. Local linear RD estimates reported in the table are based on the predicted CCT bandwidth for each outcome using either triangular or uniform kernel functions. Notably, all nine outcomes are statistically insignificant at conventional levels. This is in line with our identifying assumption and indicates that observable characteristics of students on either side of the cutoff are similar. This 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 and, thus, can be attributed to the probation policy.

Finally, as noted in Barreca, Lindo, and Waddell (2016), even if heaping were not due to manipulation, spikes in the density function of the running variable could still potentially bias estimates. As a result, in Section 5, we complement our main RD estimates with those from 'Donut' RD regressions that involve dropping heaped observations at the cutoff. Our findings remain unchanged.

5 Academic and Labor Market Impacts of Probation

5.1 Main Results

We begin by examining the effects of academic probation on student outcomes at university. Specifically, we focus on first-year GPA, dropout rates at the end of the first year and six-year graduation rates.[4] Results are summarized graphically in Figure 2. Specifically, we detect no discernible discontinuity on first-year GPA as shown in Figure 2a. On the other hand, visual evidence presented in Figure 2b and Figure 2c suggests that first-year dropout and six-year graduation rates have been affected by probation status, i.e. scoring just below the probation GPA threshold of 2.0.

Next, we move to more formal evidence for academic outcomes based on RD estimates from local linear regressions. These are reported in Table 2. Estimates presented in columns (1), (2) and (3) of the first Panel of Table 2 are in line with the visual evidence; probation has no statistically significant impact on first-year GPA but it increases first-year dropout rates by 8.7 percentage points. It also lowers six-year graduation by 9.2 percentage points—significant at the 10% level. While these estimates are based on

4. Throughout our analysis, we exclude first-quarter (Q1) GPA in our first-year GPA outcome. We do so because our running variable is Q1 GPA. In addition, we focus on first-year GPA since there is relatively less attrition in year one compared to later years, which moderates the concern of attrition bias.

bandwidths chosen from the CCT optimal bandwidth selector, we present estimates for a range of bandwidths ranging from 0.25 to 1 GPA point in Appendix Figures A1a, A1b and A1c. These estimates are presented alongside their corresponding upper and lower 95% confidence intervals. Notably, first-year GPA remains statistically insignificant regardless of bandwidth choice. The estimates on first-year dropout are more or less stable hovering around the 8 percentage point mark for bandwidths greater than 0.4 GPA points on either side of the cutoff. Estimates for six-year graduation are remarkably stable (≈ 10 percentage point reduction), but only attain statistical significance (at the 5% level) for bandwidths greater than 0.6.

We next investigate whether these documented effects persist to the longer run by looking at labor market outcomes. We focus on employment and earnings outcomes. These data are stacked and reported at ages 28 to 33. [5] Accordingly, standard errors are clustered at the individual level for regressions involving these outcomes. We begin with visual evidence presented in Figure 2. We find no visual evidence of a discontinuity in employment likelihood at the probation threshold (Figure 2d) but we do find suggestive evidence of an effect on logged earnings (Figure 2e). Corresponding regression estimates, presented in the first row of columns (4) and (5) in Table 2, indicate that probation has no statistically significant impact on employment or log earnings; though the earnings estimate is both negative (-14.6 percent) and large in magnitude. Estimates remain statistically insignificant and, for the most part, similar in magnitude regardless of bandwidth choice as shown in Appendix Figures A1d and A1e.

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, Chingos and McPherson, 2009; Smith, Pender and Howell, 2013). We therefore next 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.

We begin by examining whether academic outcomes differ by subgroup. Notably, visual evidence presented in Panels (a) and (b) of Figure 3 show no meaningful discernible differential effects on first-year GPA between groups. However, as shown in panels (c) through (f) of Figure 3, there exists a stark difference in first-year dropout and six-year graduation rates at the cutoff between both subgroups. In particular, the previously documented statistically significant impacts on first-year dropout and graduation rates are mainly driven by low-income students. Indeed, corresponding regression estimates pre-

5. As a robustness check, we later report estimates from specifications where we define labor market outcomes at 25 to 55 quarters, i.e. 4 to 13 years, after university enrollment and the results remain unchanged.

sented in columns (2) and (3) of Table 2 indicate that low-income students are 10.6 percentage points more likely to dropout after first year at university and are 21.7 percentage points ($\approx$ 33 percent) less likely to graduate if placed on probation. Conversely, high-income students are largely unaffected. RD estimates from column (1) of Table 2 also suggest that low-income students face a larger GPA penalty during their first year, as compared to higher-income students; though these estimates are not statistically significant. These findings, particularly on disparate first-year dropout and graduation rates, are robust to bandwidth choice as shown in Panels (a) through (f) of Appendix Figure A2.

We check whether these differential effects persist into the labor market. Visual evidence presented in Figures 3g, 3h, 3i and 3j show that the unequal effects of probation extend to the long run. While no subgroup is affected by employment likelihood, we observe a large and discernible discontinuity in earnings at the probation threshold for low-income students (Figure 3i). No such pattern is apparent for high-income students (Figure 3j). RD estimates, presented in columns (4) and (5) of Table 2, confirm this visual assessment and indicate that students from lower-income households experience a 38.6 percent reduction in earnings when exposed to probation. These results are robust to bandwidth choice as shown in the last four figures of Appendix Figure A2.[6] Finally, we present estimates on other labor market outcomes. Specifically, in Appendix Table A2, we look at total quarterly earnings (including zeroes) as well as the likelihood of receiving unemployment insurance. We find that low-income students, in particular, have lower average quarterly earnings and are 4.6 percentage points more likely to have received unemployment insurance at the ages of 28 to 33.

Finally, it is important to recognize that the confidence intervals around the labor market estimates are sometimes large, which is a consequence of a smaller sample. Nevertheless, the weight of findings we present suggests that low-income students bear the full brunt of academic probation as indicated by significantly higher first-year dropout rates as well as lower graduation rates and future earnings. High-income students are largely unaffected.

5.2 Robustness and Specification Checks

We complement the above analysis with some additional specification checks. First, we consider the robustness of our initial labor market estimates by taking the average of quarterly employment and earnings as the outcome—as opposed to stacked. Results are presented in Appendix Table A3 and remain quantitatively and qualitatively similar. We also check whether our results are sensitive to the choice of kernel function by re-estimating all main outcomes using a uniform kernel. These results are summarized in Appendix Table A4 and conclusions remain unchanged. As a further specification check,

6. Estimates on low-income students' earnings decrease slightly for higher bandwidth choices, but remain statistically significant throughout.

we move beyond labor market outcomes at a fixed age range and instead re-conduct our main analysis using employment and earnings 25 to 55 quarters post university enrollment (i.e., roughly 4 to 14 years after university entry).[7] Results are summarized in Appendix Table A5 and remain very similar to our main specification.

Additionally, we present estimates from a 'Donut' RD that involves dropping all observations at the heaped probation cutoff of 2.0. We summarize these 'Donut' estimates for all outcomes and subgroups of interest in Appendix Table A6.[8] Precision is worse for all specifications, which is to be expected, given the reduced sample size in this exercise. However, the magnitudes are similar for most estimates and our core finding remains the same; probation policy has a significant negative impact on lower-income students' outcomes at university and beyond, while high-income students are unaffected.

Probation could bias earnings estimates by inducing out-of-state migration, misclassifying out-of-state earnings as unemployment. However, out-of-state migration in California is low (7.2% within five years according to Foote and Stange, 2022). Nonetheless, to address this issue, we follow recommendations from Foote and Stange (2022), focusing on log earnings for student-quarters with positive earnings. While estimates for this outcome could be affected by differential sample selection, Foote and Stange (2022) note that this is often preferable to incorrectly assuming that the portion of zero-earning observations who have migrated are not working. Additionally, in Table 2, we show that probation has no impact on in-state employment likelihood, even for low-income students most affected by its earnings penalties.

6 Discussion and Conclusion

This paper documents a substantial graduation and earnings penalty for students placed on academic probation, particularly for those from low-income families. To better understand why, we examine: (1) the timing of the probation-induced attrition, (2) two additional contemporaneous outcomes—a proxy for financial aid eligibility and major switching—and (3), the evolution of wages from university entry up to 12 years post entry.

To begin, Appendix Table A8 reports RD estimates for a series of persistence outcomes by year from entry up to year six. This outcome takes the value of one if a student is enrolled in that year or graduated, and zero otherwise. Consistent with our main findings, column (1) shows that probation has a large negative effect on year two completion for the full sample (row 1), and for the low-income group (row 2). That is, students who

7. While this increases precision, using earlier labor market data has the trade-off of also potentially increasing noise, as early earnings are known to be a noisy measure of potential earnings (Hoekstra, 2009).

8. We also conduct the 'Donut' analysis for our alternative way of measuring labor market outcomes; 25 to 55 quarters from university enrollment. These results are summarized in Appendix Table A7.

marginally qualify for probation are 12.3 percentage points less likely to complete year two, and this estimate is a large 16.1 percentage points for students from low-income backgrounds.

After year two, persistence is moderately stable through year six. This pattern is particularly stable for students from low-income backgrounds (row 2). These findings indicate that most of the dropout for low-income students occurs in the first two years post probation as we find little evidence of a delayed effect; estimates are not growing across years. This immediate probation-induced dropout for low-income students then translates to lower graduation rates at this institution as previously shown in Table 2. In line with the main findings, probation does not appear to impact the persistence of high-income students.

Next, we consider two possible channels that could explain our dropout findings: financial aid eligibility and major switching behavior. It is possible that having below a 2.0 GPA leads to the loss of financial aid which, in turn, disproportionately causes low-income students to dropout. At this university, students become ineligible for federal financial aid 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 A9, 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.

Another plausible reason for our disparate findings may be that higher-income students "adjust" their majors as a result of academic probation, as opposed to dropping out altogether, like their lower-income counterparts. Column (2) of Table A9 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.

Finally, we analyze wage dynamics for students exposed to probation compared to those not exposed using RD estimates from one to 12 years post-entry (Figure A5). During the first year, when both groups remain full-time students, there are no significant wage differences. However, a divergence emerges in the second year, with probation-exposed students earning about 20% more, likely due to a transitional period of higher earnings following dropout. This gap disappears by years three to five, suggesting against a counterfactual where probation-induced dropouts permanently enter low-skill jobs. In the long run (years 5–12), probation-exposed students earn less, though differences are not statistically significant.

Focusing on low-income students (Figure A5b), the wage patterns are more pronounced. Probation-exposed students earn up to 40% more in year two but see earnings decline significantly starting in year five, with deficits of 40–50% compared to peers through year 12. No similar patterns are observed for high-income students (Figure A5c). These results suggest that low-income probation dropouts temporarily enter the labor market before likely enrolling in less selective four-or two-year institutions, leading to substantially lower earnings by age 30 when wages stabilize.[9]

In conclusion, findings from this paper indicate that academic probation carries a large, and previously undocumented, long-run penalty for students. This burden disproportionately impacts low-income students who are more likely to dropout when exposed to probation compared to their high-income counterparts. This substantially impacts their career earnings which do not seem to recover many years after initial enrollment. These findings highlight the potential for academic probation—a near universal policy affecting up to 20% of all first-year students at U.S. colleges—to exacerbate existing inequalities.

9. According to Grade Reports, which draws on data from the U.S. Department of Education's College Score Card, the institution in our study scores a 90 out of 100 on the "best colleges by earnings one year out of college". The ranking is reported here: https://www.gradreports.com/rankings/california-polytechnic-state-universitysan-luis-obispo.

References

[1] Bailey, Martha J., and Susan M. Dynarski. 2011. Gains and gaps: Changing inequality in US college entry and completion. No. w17633. *NBER Working Paper*.

[2] Barreca, Alan I., Jason M. Lindo, and Glen R. Waddell. 2016. Heaping-induced bias in regression discontinuity designs. *Economic Inquiry* 54, no. 1:268-293.

[3] Bénabou, Roland, and Jean Tirole. 2000. Self-confidence and social interactions. *Working Paper*.

[4] Bénabou, Roland, and Jean Tirole. 2003. Intrinsic and extrinsic motivation. *The Review of Economic Studies* 70, 489–520.

[5] Black, Sandra E., Jeffrey T. Denning, Lisa J. Dettling, Sarena Goodman, and Lesley J. Turner. 2023. Taking it to the limit: Effects of increased student loan availability on attainment, earnings, and financial well-being. *American Economic Review* 113 (12): 3357-3400.

[6] Black, Sandra E., Jeffrey T. Denning, and Jesse Rothstein. 2023. Winners and losers? the effect of gaining and losing access to selective colleges on education and labor market outcomes. *American Economic Journal: Applied Economics* 15 (1): 26-67.

[7] Bleemer, Zachary and Aashish Mehta. 2024. College major restrictions and student stratification. *Working Paper*

[8] Bound, John, Michael F. Lovenheim, and Sarah Turner. 2010. Why have college completion rates declined? An analysis of changing student preparation and collegiate resources. *American Economic Journal: Applied Economics* 2 (3): 129-157.

[9] Bowen, William G., Matthew M. Chingos, and Michael S. McPherson. 2009. *Crossing the finish line: Completing college at America's public universities.*

[10] Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. Robust nonparametric confidence intervals for regression discontinuity designs. *Econometrica* 82 (6): 2295-2326.

[11] Canaan, Serena, Stefanie Fischer, Pierre Mouganie and Geoffrey C. Schnorr. 2024. Keep me in, coach: The short- and long-term effects of a university coaching intervention. *Working Paper*.

[12] Canaan, Serena, and Pierre Mouganie. 2018. Returns to education quality for low-skilled students: Evidence from a discontinuity. *Journal of Labor Economics* 36 (2): 395-436.

[13] Casey, Marcus D., Jeffrey Cline, Ben Ost, and Javaeria A. Qureshi. 2018. Academic probation, student performance, and strategic course-taking. *Economic Inquiry* 56, no. 3: 1646-1677.

[14] Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2020. Income segregation and intergenerational mobility across colleges in the United States. *The Quarterly Journal of Economics* 135 (3): 1567-1633.

[15] Chu, Yu-Wei Luke, and Harold E. Cuffe. 2024. Do academically struggling students benefit from continued student loan access? Evidence from university and beyond. *Review of Economics and Statistics* 106, (1): 68-84.

[16] Deming, David J., and Christopher R. Walters. 2017. The impact of price caps and spending cuts on US postsecondary attainment. No. w23736. *NBER Working Paper*.

[17] Dynarski, Susan, Aizat Nurshatayeva, Lindsay C. Page, and Judith Scott-Clayton. 2023. Addressing nonfinancial barriers to college access and success: Evidence and policy implications. In *Handbook of the Economics of Education*, vol. 6, pp. 319-403.

[18] Dynarski, Susan, Lindsay Page, and Judith Scott-Clayton. 2023. College costs, financial aid, and student decisions. In *Handbook of the Economics of Education*, vol. 7, pp. 227-285.

[19] Dong, Yingying. 2019. Regression discontinuity designs with sample selection. *Journal of Business & Economic Statistics* 37, no. 1: 171-186.

[20] Fletcher, Jason M., and Mansur Tokmouline. 2018. The effects of academic probation on college success: Regression discontinuity evidence from four texas universities. *Working Paper*.

[21] Foote, Andrew, and Kevin M. Stange. 2022. Attrition from administrative data: Problems and solutions with an application to postsecondary education. *National Bureau of Economic Research No. w30232.*

[22] Gurantz, Oded. 2022. Impacts of state aid for nontraditional students on educational and labor market outcomes. *Journal of Human Resources* 57.1: 241-271.

[23] Hastings, J.S., Neilson, C.A., Zimmerman, S.D. 2013. Are some degrees worth more than others? Evidence from college admission cutoffs in Chile. *NBER Working Paper 19241*.

[24] Hoekstra, Mark. 2009. The effect of attending the flagship state university on earnings: A discontinuity-based approach. *The Review of Economics and Statistics* 91 (4): 717-724.

[25] Imbens, Guido W., and Thomas Lemieux. 2008. Regression discontinuity designs: A guide to practice. *Journal of Econometrics* 142, no. 2:615-635.

[26] Kolesár, Michal, and Christoph Rothe. 2018. Inference in regression discontinuity designs with a discrete running variable. *American Economic Review* 108 (8): 2277-2304.

[27] Lee, David S., and Thomas Lemieux. 2010. Regression discontinuity designs in economics. *Journal of Economic Literature* 48 (2): 281-355.

[28] Lindo, Jason M., Nicholas J. Sanders, and Philip Oreopoulos. 2010. Ability, gender, and performance standards: Evidence from academic probation. *American Economic Journal: Applied Economics* 2(2): 95-117.

[29] McCrary, Justin. 2008. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics* 142, no. 2:698-714.

[30] Mountjoy, Jack. 2024. Marginal Returns to Public Universities. No. w32296. *NBER Working Paper*.

[31] Ost, Ben, Weixiang Pan, and Douglas Webber. 2018. The returns to college persistence for marginal students: Regression discontinuity evidence from university dismissal policies. *Journal of Labor Economics* 36, no. 3: 779-805.

[32] Roderick, M., Jenny Nagaoka, Vanessa Coca, Eliza Moeller, Karen Roddie, Jamiliyah Gilliam, and Desmond Patton. 2008. From high school to the future: Potholes on the road to college. Consortium on Chicago School Research, University of Chicago.

[33] Smith, Jonathan, Joshua Goodman, and Michael Hurwitz. 2020. The economic impact of access to public four-year colleges. No. w27177. *NBER Working Paper*.

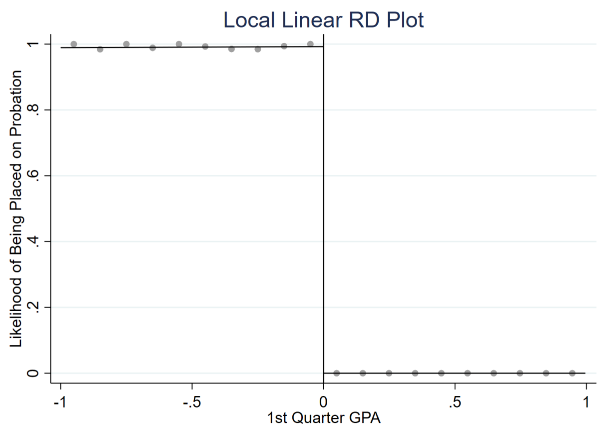
[34] Smith, Jonathan, Matea Pender, and Jessica Howell. 2013. The full extent of Academic undermatch. *Economics of Education Review* 32:247-261.

[35] Staley, David J. 2022. How to Fix the Problems with Academic Probation. *Inside Higher Ed, March 23, 2022*. accessed at: https://www.insidehighered.com/views/2022/03/23/how-fix-problems-academic-probation-opinion.

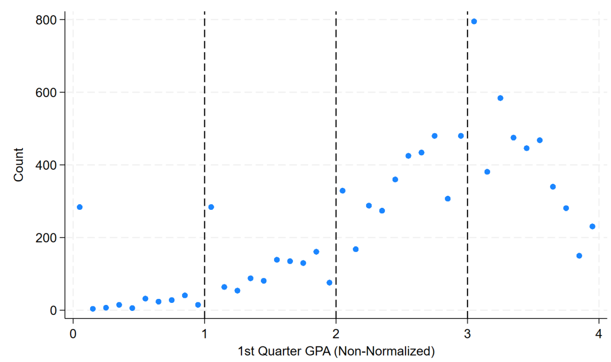
[36] U.S. Bureau of Labor Statistics. 2023. College Enrollment and Work Activity of Recent High School and College Graduates — 2023. Last modified April 23, 2024. https://www.bls.gov/news.release/hsgec.nr0.htm.

[37] Zimmerman, Seth D. 2014. The returns to college admission for academically marginal students. *Journal of Labor Economics* 32, no. 4:711-754.

A Figures

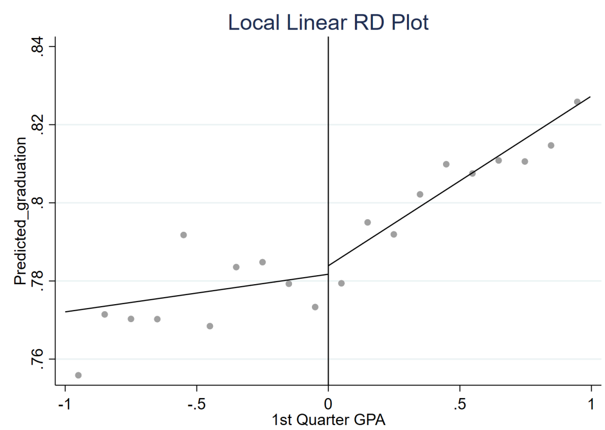


(a) Likelihood of Being Placed on Probation



(b) Distribution of Q1 GPA

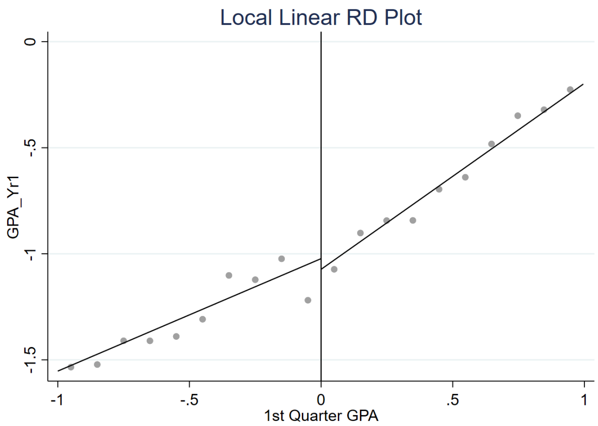
(c) Predicted 1st Year GPA



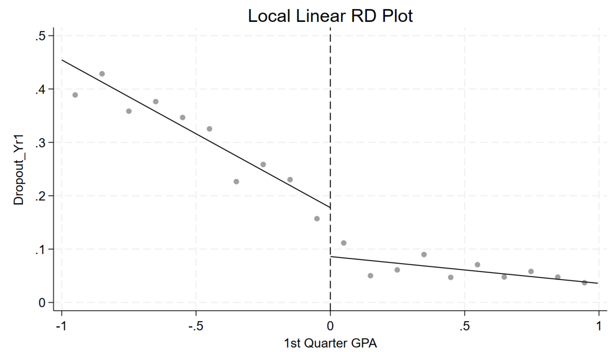
(d) Predicted Graduation Rates

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Circles represent local averages over a 0.1 GPA range. The running variable is first quarter GPA. Figures in panels (a), (c) (d) are drawn using a linear fit on either side of the cutoff. Predicted outcomes in panels (c) and (d) based on the following controls: SAT scores, gender dummy, non-white dummy, remedial math dummy, remedial English dummy, pell eligibility, EFC scores, mothers' and fathers' college graduation dummy.

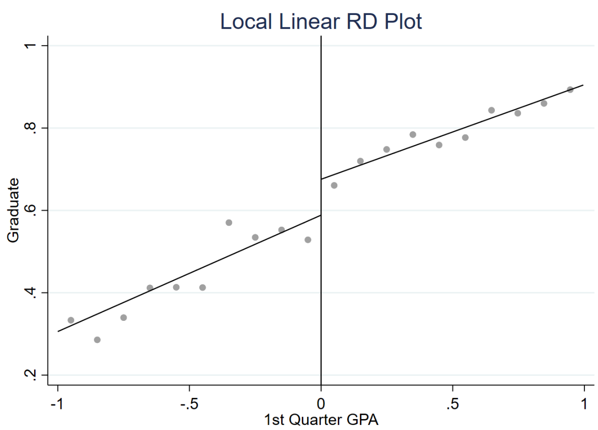
Figure 2: Visual RD Evidence for Academic and Labor Market outcomes



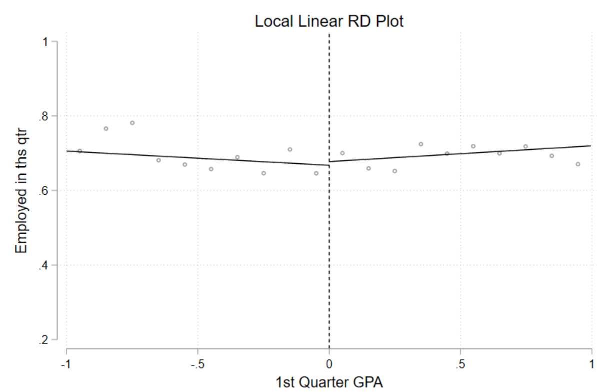
(a) Q2+Q3 GPA



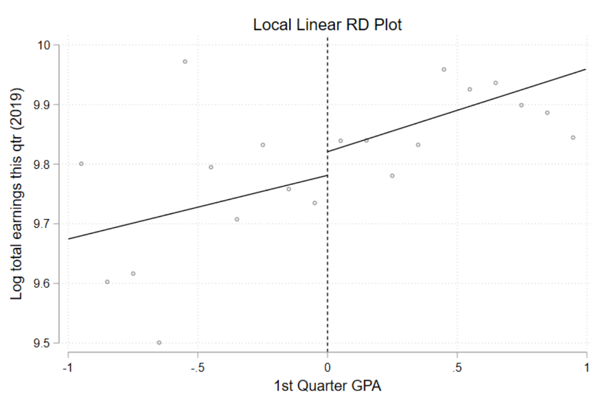
(b) First-Year Dropout



(c) Six-year Graduation Rates



(d) Likelihood of Employment

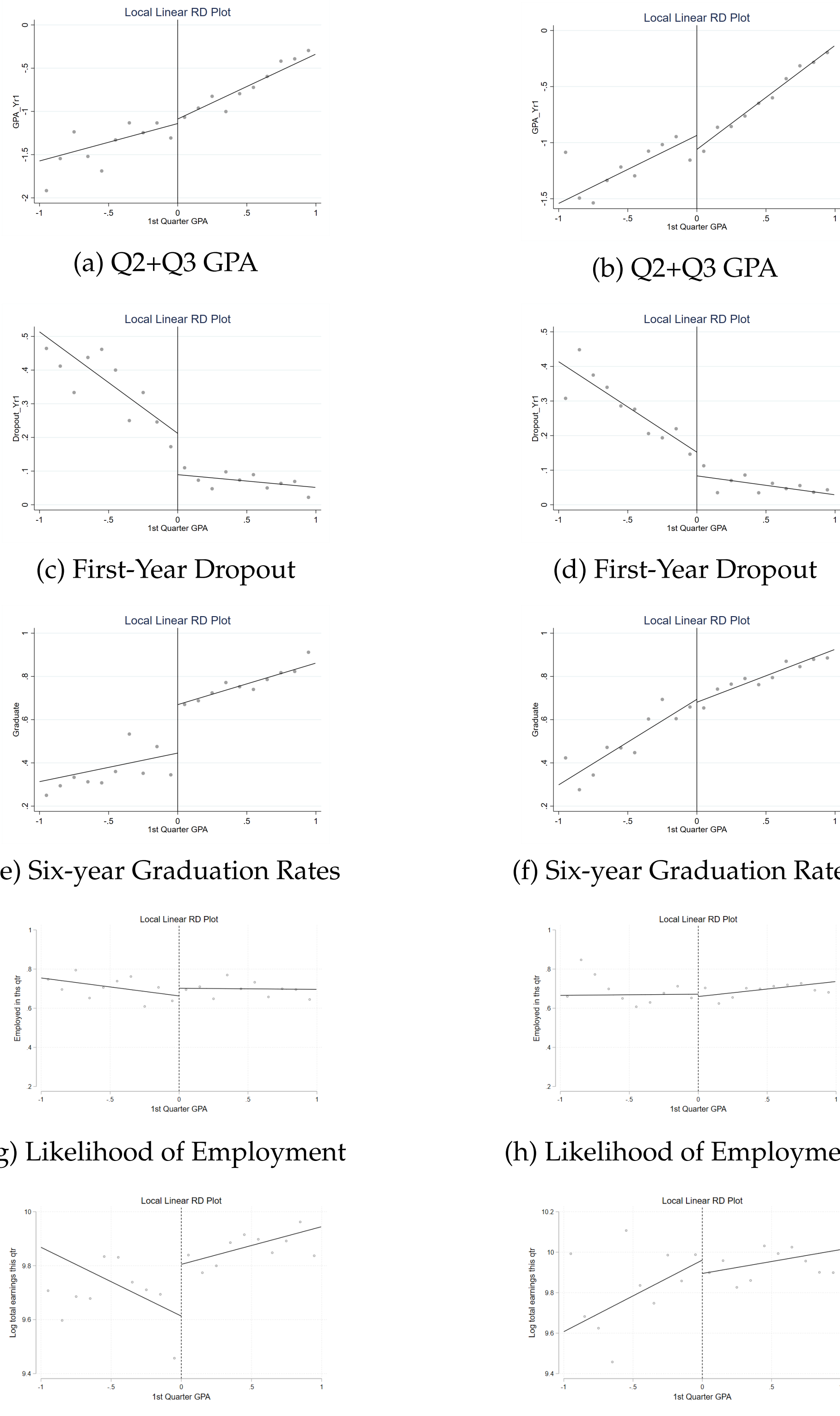


(e) Log Earnings

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008, and 2009 (select faculties). Circles represent local averages over a 0.1 GPA range. The running variable is first quarter GPA. Figures are drawn using a linear fit on either side of the cutoff. GPA is standardized by cohort and reported for all students. Figures in panels (d) and (e) are based on stacked labor market outcomes at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

Figure 3: Visual RD Evidence for Main Outcomes Based on Income Status

Low-Income | High-Income



(a) Q2+Q3 GPA

(b) Q2+Q3 GPA

(c) First-Year Dropout

(d) First-Year Dropout

(e) Six-year Graduation Rates

(f) Six-year Graduation Rates

(g) Likelihood of Employment

(h) Likelihood of Employment

(i) Log Earnings

(j) Log Earnings

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. Circles represent local averages over a 0.1 GPA range. The running variable is first quarter GPA. Figures are drawn using a linear fit on either side of the cutoff. GPA is standardized by cohort and reported for all students. Figures in panels (e) through (h) are based on stacked labor market outcomes at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

B Tables

Table 1: Summary Statistics

	Whole Sample	Marginal Sample
	(1)	(2)
Demographic and academic controls		
SAT scores	1189.72	1163.57
	(129.96)	(130)
Female	0.47	0.42
Non-white	0.33	0.37
Remedial Math	0.04	0.05
Remedial English	0.10	0.13
Pell Grant Eligible	0.13	0.15
EFC $< \$30,000$	0.34	0.36
Father College +	0.81	0.78
Mother College +	0.82	0.80
Observations (Individuals)	8,632	4,595
Academic Outcomes		
Likelihood of First-year Dropout	0.09	0.10
	(0.29)	(0.31)
6-year Graduation	0.80	0.74
	(0.40)	(0.44)
Observations (Individuals)	8,632	4,595
Labor Market Outcomes		
Employed in Quarter	0.67	0.69
	(0.47)	(0.46)
Quarterly Earnings	18,083.52	17,685.15
	(27,705.87)	(27,147.24)
Cumulative Quarters of Experience	30.47	31.07
	(13.83)	(13.67)
Received Unemployment Insurance in Quarter	0.02	0.03
	(0.15)	(0.17)
Observations (Individuals)	8,608	4,578
Observations (Quarters)	163,720	88,068

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Means and standard deviations (reported) in parentheses. The marginal sample in column (2) represents all students scoring between 1 and 3 GPA points during the first semester at university. Labor market outcomes are reported at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

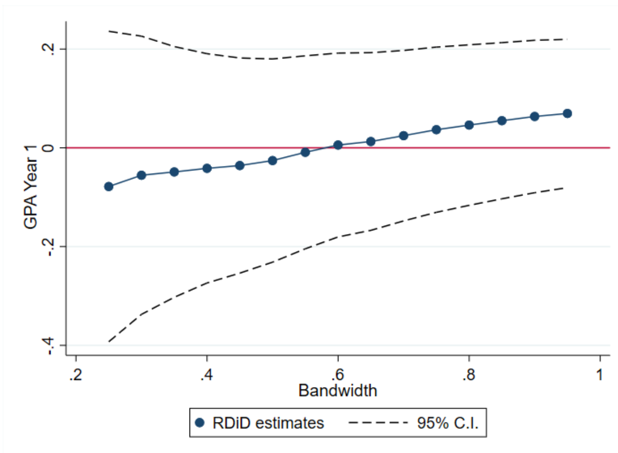
Table 2: RD Estimates of Probation on Academic and Labor Market Outcomes

	GPA (Q2+Q3) (1)	**Year-1 Dropout** (2)	**6-year Graduation** (3)	**Employed** (4)	**Log Earnings** (5)
All					
Probation Effect	-0.040	0.087**	-0.092*	-0.0005	-0.146
	(0.113)	(0.041)	(0.054)	(0.047)	(0.108)
Observations	1,659	1,898	1,998	20,242	18,921
CCT Bandwidth	0.439	0.494	0.514	0.434	0.379
Low SES					
Probation Effect	-0.173	0.106*	-0.217***	-0.037	-0.386**
	(0.188)	(0.063)	(0.079)	(0.059)	(0.190)
Observations	578	891	762	17,570	7,247
CCT Bandwidth	0.408	0.587	0.502	0.632	0.349
High SES					
Probation Effect	0.082	0.069	0.010	0.031	0.036
	(0.123)	(0.053)	(0.068)	(0.065)	(0.115)
Observations	1,371	1,194	1,251	20,242	12,171
CCT Bandwidth	0.567	0.484	0.531	0.434	0.425
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Selector	CCT	CCT	CCT	CCT	CCT

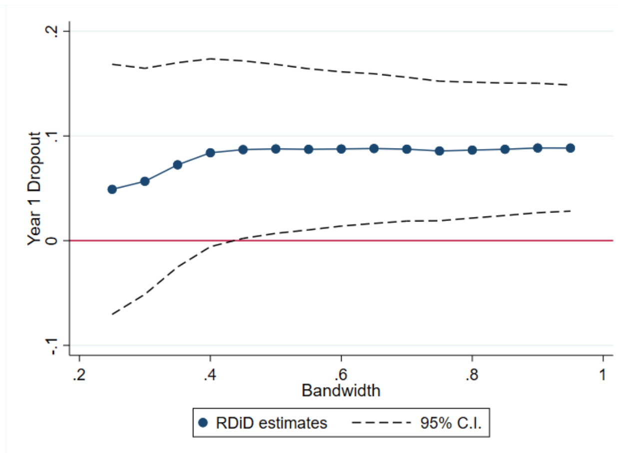
Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Low-income students are those with an Expected Family Contribution of less than $30,000 while high-income students are those at or above this threshold. Each point estimate is from a separate 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. Labor Market outcomes are stacked and reported at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Robust standard errors are reported in parentheses in columns (1), (2) and (3). Clustered standard errors at individual level are reported in parentheses in columns (4) and (5).*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C Appendix Figures

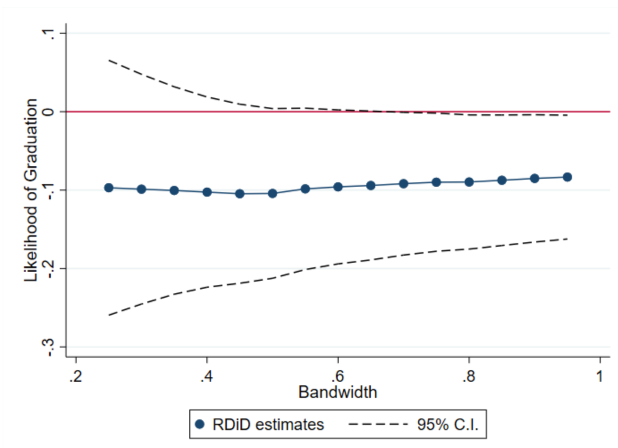
Figure A1: Robustness of Bandwidth Choice for Academic and Labor Market Outcomes



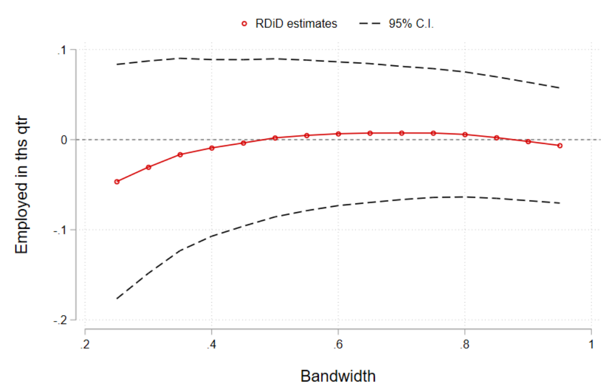
(a) Q2+Q3 GPA



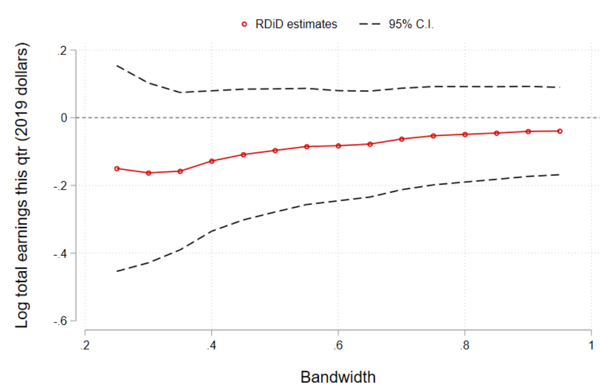
(b) First-Year Dropout



(c) Six-year Graduation Rates



(d) Likelihood of Employment



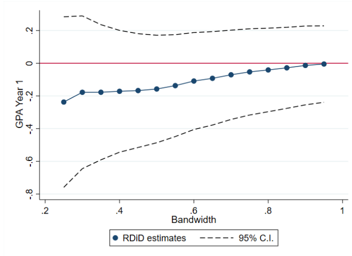
(e) Log Earnings

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008, and 2009 (select faculties). 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 A1 (d) and (e) are based on stacked labor market outcomes at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

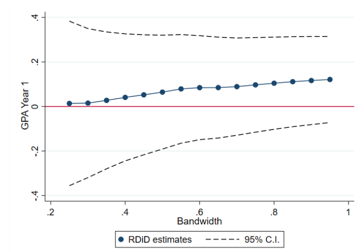
Figure A2: Robustness of Bandwidth Choice for Main Outcomes by Income Status

Low-Income

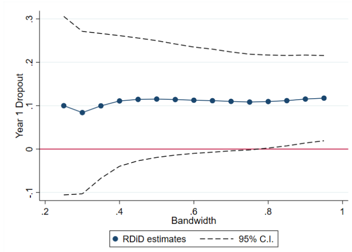
High-Income



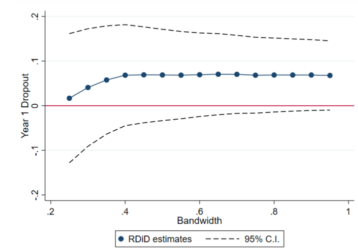
(a) Q2+Q3 GPA



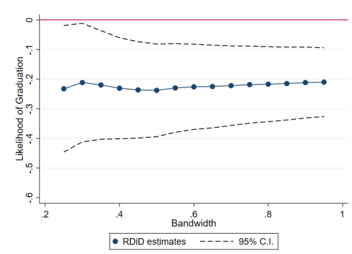
(b) Q2+Q3 GPA



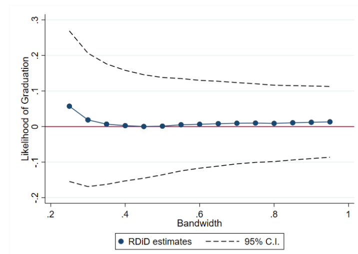
(c) First-Year Dropout



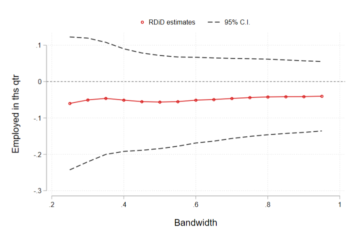
(d) First-Year Dropout



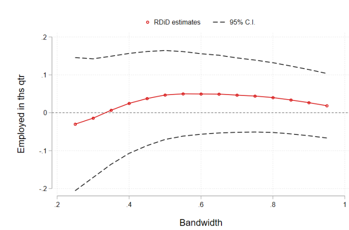
(e) Six-year Graduation Rates



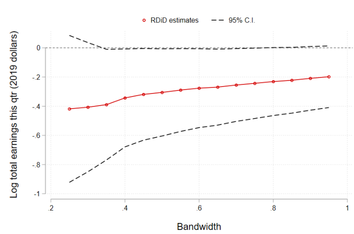
(f) Six-year Graduation Rates



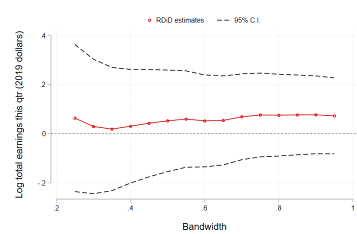
(g) Likelihood of Employment



(h) Likelihood of Employment



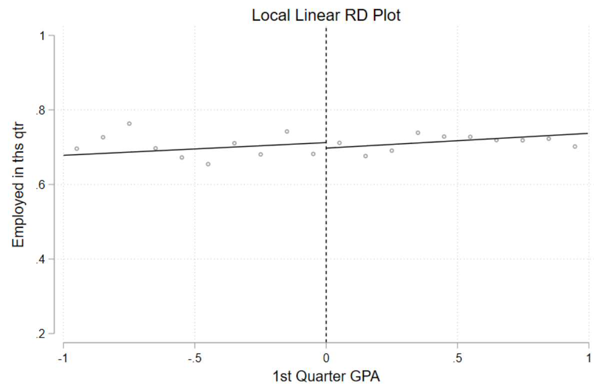
(i) Log Earnings



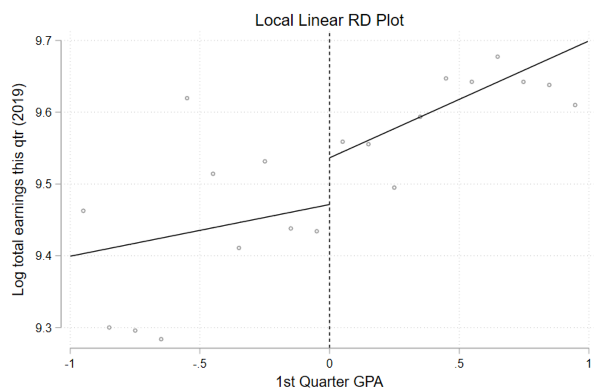
(j) Log Earnings

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. Scatter points represent estimates from local linear regressions ranging from 0.25 to 1 GPA point on either side of the cutoff. The dashed lines correspond to 95% confidence intervals. GPA is standardized by cohort and reported for all students. Figures A1 (g) through (j) are based on stacked labor market outcomes at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

Figure A3: Labor Market Probation Effects 25 to 55 quarters after University Enrollment



(a) Likelihood of Employment



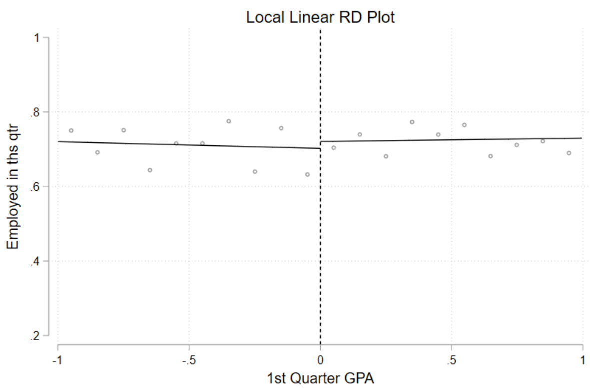
(b) Log Earnings

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Circles represent local averages over a 0.1 GPA range. The running variable is first quarter GPA. Figures are drawn using a linear fit on either side of the cutoff. Labor market figures are based on stacked labor market outcomes 25 to 55 quarters, i.e. 4 to 13 years, after university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

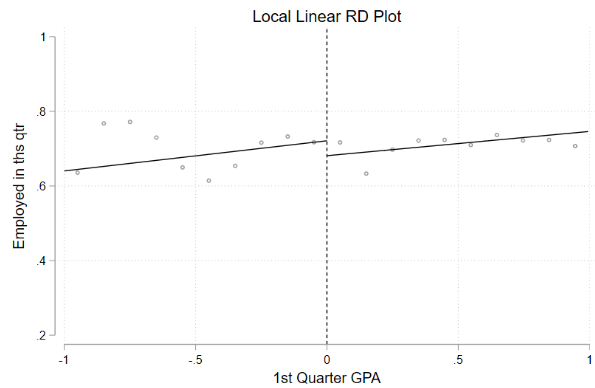
Figure A4: Labor Market Probation Effects by Income Status 25 to 55 quarters from University Enrollment

Low-Income

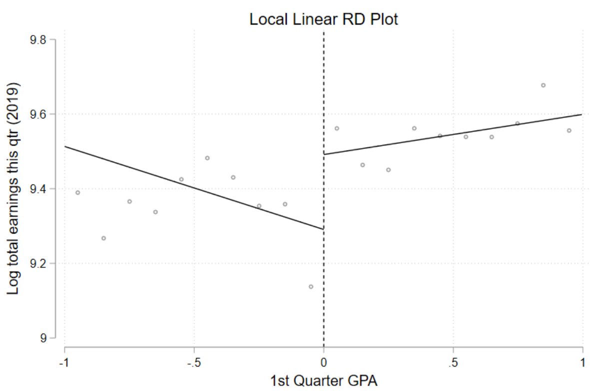
High-Income



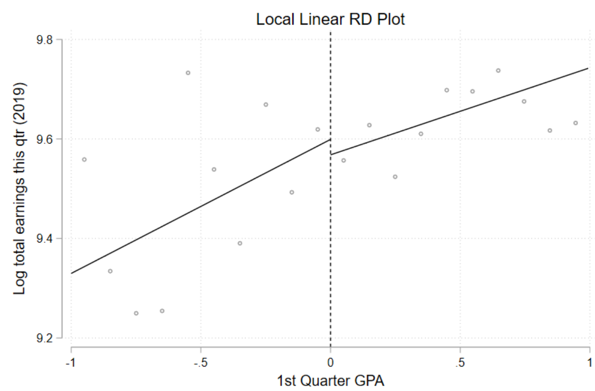
(a) Likelihood of Employment



(b) Likelihood of Employment



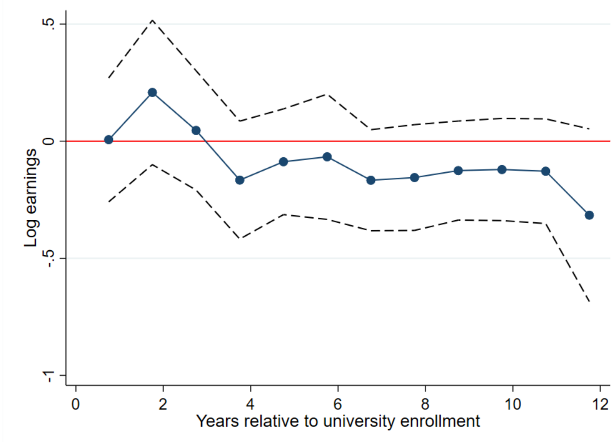
(c) Log Earnings



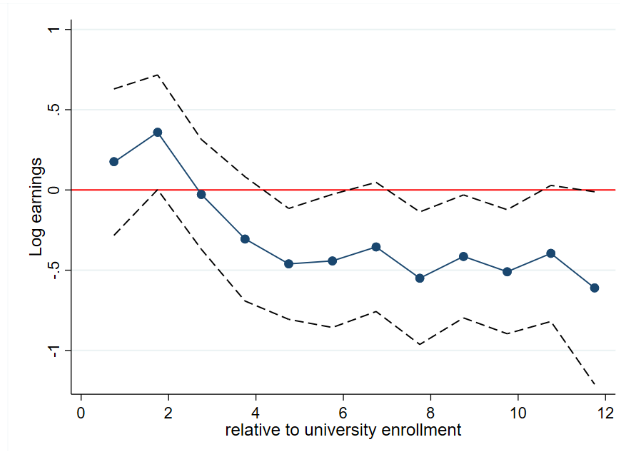
(d) Log Earnings

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties) 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. Circles represent local averages over a 0.1 GPA range. The running variable is first quarter GPA. Figures are drawn using a linear fit on either side of the cutoff. Labor market figures are based on stacked labor market outcomes 25 to 55 quarters, i.e. 4 to 13 years, after university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

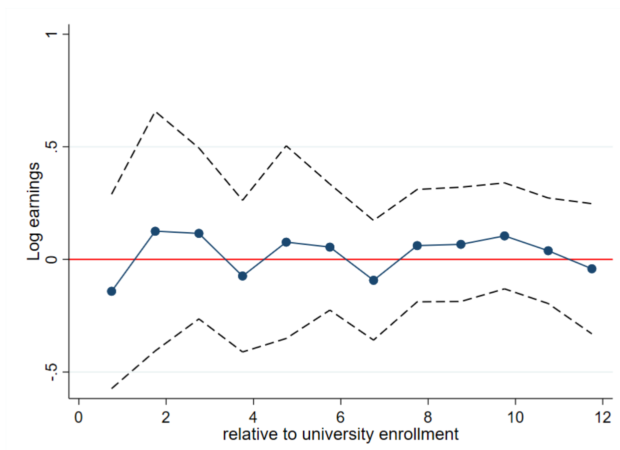
Figure A5: RD Wage Estimates Relative to University Enrollment Year



(a) All students



(b) Low-income students



(c) High-income students

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. Scatter points represent RD estimates on the effects of probation on log earnings relative to university year enrollment. Dashed lines represent upper and lower 95% confidence intervals. RD estimates are from local linear regressions using a triangular kernel and CCT bandwidth selector.

D Appendix Tables

Table A1: Baseline Covariates Balance Check for RD Research Design

	(1) SAT Scores	(2) Female	(3) Non-White	(4) Remedial Math	(5) Remedial English	(6) Pell elig.	(7) EFC $<$ \$30K	(8) Father college	(9) Mother college
Triangular Kernel	21.408	-0.054	-0.042	-0.041	0.002	0.005	0.023	-0.055	-0.007
	(13.641)	(0.052)	(0.049)	(0.025)	(0.043)	(0.044)	(0.055)	(0.057)	(0.055)
Uniform Kernel	10.149	-0.022	-0.042	-0.015	-0.007	0.007	0.023	-0.025	0.012
	(13.904)	(0.039)	(0.051)	(0.023)	(0.042)	(0.042)	(0.052)	(0.053)	(0.052)
CCT Bandwidth (Triangular)	0.511	0.358	0.633	0.431	0.463	0.521	0.515	0.392	0.420
CCT Bandwidth (Uniform)	0.426	0.630	0.478	0.463	0.425	0.442	0.453	0.349	0.341
Observations (Triangular)	1,899	1,385	2,483	1,586	1,779	2,003	1,996	1,459	1,525
Observations (Uniform)	1,491	2,469	1,869	1,779	1,535	1,738	1,759	1,345	1,330

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. All regressions include cohort and college fixed effects. All local linear RD regressions use a triangular or uniform kernel function. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: RD Estimates of Probation on Other Labor Market Outcomes

	Quarterly Earnings	Receive Unemployment Insurance
All		
Probation Effect	-109.92	0.022**
	(2353)	(0.010)
Observations	33,794	33,202
CCT Bandwidth	0.448	0.433
Low SES		
Probation Effect	-7,464*	0.046**
	(4,105)	(0.019)
Observations	8,040	13,732
CCT Bandwidth	0.285	0.472
High SES		
Probation Effect	4,153	0.005
	(3,043)	(0.009)
Observations	24,932	20,362
CCT Bandwidth	0.541	0.437
Kernel	Triangular	Triangular
Bandwidth Selector	CCT	CCT

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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 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. Labor market outcomes are stacked at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors at individual level are reported in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: RD Labor Market Effects of Probation Averaged from Ages 28 to 33

	Employed	**Log Earnings**
All		
Probation Effect	0.009	-0.192
	(0.046)	(0.150)
Observations	1,761	1,140
CCT Bandwidth	0.455	0.357
Low SES		
Probation Effect	-0.025	-0.413*
	(0.059)	(0.225)
Observations	885	473
CCT Bandwidth	0.582	0.362
High SES		
Probation Effect	0.033	0.052
	(0.066)	(0.168)
Observations	873	758
CCT Bandwidth	0.399	0.426
Kernel	Triangular	Triangular
Bandwidth Selector	CCT	CCT

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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 regression. The CCT bandwidth selector is used to select 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. Labor market outcomes are averaged at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors at individual level are reported in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: RD Labor Market Effects of Probation at Ages 28 to 33—Uniform Kernel

	GPA (Q2+Q3) (1)	**Year-1 Dropout** (2)	**6-year Graduation** (3)	**Employed** (4)	**Log Earnings** (5)
All					
Probation Effect	-0.007	-0.102**	0.080	0.012	-0.116
	(0.096)	(0.044)	(0.049)	(0.047)	(0.095)
Observations	1,816	1,438	2,004	26,728	18,052
CCT Bandwidth	0.493	0.380	0.522	0.36	0.353
Low SES					
Probation Effect	0.203	-0.123*	0.192***	-0.053	-0.318*
	(0.165)	(0.070)	(0.072)	(0.062)	(0.186)
Observations	583	575	762	13,086	5,606
CCT Bandwidth	0.418	0.373	0.506	0.454	0.293
High SES					
Probation Effect	-0.097	-0.083	-0.003	0.042	0.010
	(0.127)	(0.055)	(0.067)	(0.064)	(0.114)
Observations	1,013	913	1,069	15,420	10,173
CCT Bandwidth	0.444	0.414	0.452	0.346	0.337
Kernel	Uniform	Uniform	Uniform	Uniform	Uniform
Bandwidth Selector	CCT	CCT	CCT	CCT	CCT

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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 regression. The CCT bandwidth selector is used to determine the optimal bandwidths for each regression. All local linear RD regressions use a uniform kernel function. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. Labor market outcomes are averaged at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors at individual level are reported in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: RD Labor Market Effects of Probation 25 to 55 Quarters From University Enrollment

	Employed	**Log Earnings**
All		
Probation Effect	0.031	-0.134
	(0.041)	(0.094)
Observations	54,510	38,522
CCT Bandwidth	0.459	0.457
Low SES		
Probation Effect	-0.024	-0.421***
	(0.060)	(0.172)
Observations	22,445	12,629
CCT Bandwidth	0.487	0.367
High SES		
Probation Effect	0.071	0.034
	(0.060)	(0.107)
Observations	26,971	25,126
CCT Bandwidth	0.398	0.494
Kernel	Triangular	Triangular
Bandwidth Selector	CCT	CCT

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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 regression. The CCT bandwidth selector is used to select 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. Labor Market outcomes are stacked and reported 25 to 55 quarters from university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors at individual level are reported in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: 'Donut' RD Estimates of Probation on Academic and Labor Market Outcomes

	GPA (Q2+Q3)	**Year-1 Dropout**	**6-year Graduation**	**Employed**	**Log Earnings**
	(1)	(2)	(3)	(4)	(5)
All					
Probation Effect	-0.085	0.074	-0.093	0.016	-0.170
	(0.138)	(0.047)	(0.061)	(0.052)	(0.122)
Observations	1,484	1,692	1,930	31,004	16,276
CCT Bandwidth	0.452	0.497	0.561	0.447	0.362
Low SES					
Probation Effect	-0.398	0.120*	-0.291***	-0.040	-0.395*
	(0.245)	(0.069)	(0.095)	(0.067)	(0.207)
Observations	477	831	643	15,736	6,341
CCT Bandwidth	0.392	0.626	0.495	0.584	0.340
High SES					
Probation Effect	0.119	0.024	0.041	0.045	0.010
	(0.148)	(0.060)	(0.072)	(0.071)	(0.130)
Observations	1,078	968	1,420	16,664	10,344
CCT Bandwidth	0.525	0.463	0.624	0.428	0.397
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Selector	CCT	CCT	CCT	CCT	CCT

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. 'Donut' regressions involve dropping observations at 1.9 and 2.0 exact GPA points. Each point estimate is from a separate regression. The CCT bandwidth selector is used to determine 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. Labor market outcomes are stacked and reported at ages 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Robust standard errors are reported in parentheses in columns (1), (2) and (3). Clustered standard errors at individual level are reported in parentheses in columns (4) and (5). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: 'Donut' RD Labor Market Effects of Probation 25 to 55 Quarters From University Enrollment

	Employed	**Log Earnings**
All		
Probation Effect	0.048	-0.105
	(0.048)	(0.104)
Observations	48,952	34,426
CCT Bandwidth	0.439	0.436
Low SES		
Probation Effect	-0.041	-0.433***
	(0.068)	(0.184)
Observations	20,222	11,051
CCT Bandwidth	0.472	0.356
High SES		
Probation Effect	0.092	0.062
	(0.067)	(0.119)
Observations	23,788	21,643
CCT Bandwidth	0.376	0.465
Kernel	Triangular	Triangular
Bandwidth Selector	CCT	CCT

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. 'Donut' regressions involve dropping observations at 1.9 and 2.0 exact GPA points. Each point estimate is from a separate regression. The CCT bandwidth selector is used to determine optimal bandwidths for each regression. "Donut" local linear RD regressions using a triangular kernel function are reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. Labor market outcomes are stacked and reported 25 to 55 quarters from university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors at individual level are reported in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: DiRD Estimates: Persistence by Year

	(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)
All Students	-0.123**	-0.060	-0.078	-0.093*	-0.079
	(0.055)	(0.048)	(0.057)	(0.056)	(0.052)
Low-SES	-0.161*	-0.170**	-0.211***	-0.207***	-0.188***
	(0.085)	(0.077)	(0.081)	(0.080)	(0.072)
High-SES	-0.089	0.025	0.023	0.000	0.010
	(0.066)	(0.059)	(0.070)	(0.072)	(0.070)
Observations (All)	1,525	2,363	1,765	1,867	2,128
CCT Bandwidth (All)	0.418	0.584	0.456	0.477	0.555
Observations (Low SES)	632	770	727	722	1,039
CCT Bandwidth (Low SES)	0.432	0.524	0.488	0.478	0.673
Observations (High SES)	954	1,517	1,069	1,155	1,218
CCT Bandwidth (High SES)	0.433	0.600	0.452	0.481	0.506

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. The CCT bandwidth selector is used to determine optimal bandwidths for each regression. All regressions use a triangular kernel. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9: Additional Academic Outcomes

	(1) Year 1 GPA Below 2.0	(2) Switch Major
All Students	0.045	-0.009
	(0.055)	(0.048)
Low-SES	0.081	0.027
	(0.092)	(0.054)
High-SES	0.027	-0.030
	(0.060)	(0.066)
Observations (All)	1,327	1,743
CCT Bandwidth (All)	0.356	0.445
Observations (Low SES)	553	952
CCT Bandwidth (Low SES)	0.375	0.654
Observations (High SES)	864	954
CCT Bandwidth (High SES)	0.407	0.431

Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). 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. All regressions include controls for gender, race and parents' education as well as cohort and college fixed effects. The CCT bandwidth selector is used to determine optimal bandwidths for each regression. All regressions use a triangular kernel. Robust standard errors reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.