The Role of University Policies in Exacerbating Socioeconomic Inequality

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Abstract

Academic probation is a nearly universal policy in all North American universities. Broadly defined, academic probation involves notifying low-performing students that they need to improve their GPA or will be eventually dismissed from university. Probation may widen socioeconomic gaps in educational attainment and in the labor market if it disproportionately discourages low-income students. However, it is still unclear whether probation has disparate impacts on students from different socioeconomic backgrounds. Additionally, its effects on labor market outcomes are still poorly understood. Our paper aims to fill these gaps in the literature. To do so, we draw on rich linked administrative data for all first-year students entering a large public university in the state of California from 2007 to 2009. We use a regression discontinuity design that leverages as-good-as-random variation in the likelihood that students are placed on academic probation based on a 2.0 GPA cutoff. Results indicate that academic probation has negative effects on 6-year graduation and earnings but estimates are not statistically significant at conventional levels. These overall effects mask substantial heterogeneity based on socioeconomic background. High-income students' academic and labor market outcomes are largely unaffected by probation. However, low-income students experience a significant 27.6 percentage point (42%) decrease in 6-year graduation rates and a 42% drop in earnings. Our results have important policy implications for ongoing discussions on the widening of socioeconomic gaps in the U.S.

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1 Introduction

Income mobility in the U.S. has decreased significantly over the past century. Today, children are half as likely to earn more than their parents compared to those born in the 1940s. One factor contributing to this decline is differences in higher education attainment, as a college degree remains an effective path to upward mobility (Chetty et al., 2017). While the labor market returns to a four-year degree are substantial and have been growing over time, particularly for low-income students (Hoekstra, 2009; Zimmerman, 2014; Smith, Goodman, and Hurwitz, 2020), there remains a significant gap in college completion rates between students from high- and low-income families. Among students from the bottom quartile of the income distribution, only 9% earn a bachelor's degree compared to 54% of students from the top quartile (Bailey and Dynarski, 2011).

Universities can play a critical role in promoting social mobility, however, very little is known about the policies and institutional features that produce mobility (Chetty et al. 2020). Moreover, policies and conditions may have disparate impacts on students from different socioeconomic backgrounds, especially given that students from low-income backgrounds often face non-financial barriers that impede degree completion (Dynarski et al., 2023). This paper considers the role of a universal policy in higher education, academic probation, in widening socioeconomic gaps in college completion and earnings.

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 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 and labor market outcomes. In this paper, we aim to fill this gap in the literature.

Our analysis focuses on students who first enrolled at a large and selective public four-year university in California 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). 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 32. Students are placed on academic probation if their first-quarter GPA is below a 2.0. As such, we estimate the causal effect of probation using a regression discontinuity research 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).

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. These overall effects mask substantial heterogeneity based on socioeconomic background. High-income students' academic and labor market outcomes are largely unaffected by probation. However, low-income students experience a significant 27.6 percentage point (42%) decrease in 6-year graduation rates and a 42% 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).

Relatively fewer studies have focused on identifying institutional-level factors or policies that 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. Several previous studies have looked at how academic probation affects college dropout rates, but findings are mixed. In their seminal work, Lindo et al. (2010) show that amongst 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 some U.S. universities, placement on probation has no impact on dropout rates but improves GPA in the subsequent term (Fletcher and Tokmouline, 2018; Casey et al., 2018). On the other hand, Dong (2019) finds that probation increases dropout rates for women but not for men in 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.[1] Additionally, 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 effects of probation on academic outcomes do not fade over time. Instead, the probation label results in substantial and persistent losses in earnings through age 32. Importantly,

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.

since these effects are exclusively driven by low-income students, probation exacerbates socioeconomic inequalities in the labor market.

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 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.

As with many universities in the U.S. and globally, student retention and academic mismatch is a concern for administrators at this institution. As a result, an academic probation system is in place with the goal of identifying marginal students and potentially aiding them with their progress. The probation system used at this institution closely resembles those implemented in other universities, as academic probation has become a near universal policy in higher education in North America. At this institution, academic probation is solely a function of a student's GPA. At the end of each quarter, students who have a cumulative GPA or a term GPA below 2.0 are placed on academic probation and are notified of this status by an institutional letter. Students remain on probation until their term and cumulative GPA are above the 2.0 threshold. First-year students are granted a probationary period of the first year to improve their GPA above this threshold in order to avoid dismissal from university.

While this policy is meant to serve as a well-intended wake-up call for students falling behind and/or identify students who are academically mismatched at the institution, models of intrinsic and extrinsic motivation predict that such a policy also has a discouragement effect and can lower students' motivation and confidence (Bénabou and Tirole, 2003). Empirically, the discouragement effects 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 wage 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 Insruance (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 UI 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 part of a pilot program. 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.

We begin by considering the mean demographic and academic characteristics of students in our sample. Students who enrolled at university between the years 2007 and 2009 scored an average of 1,190 points on the SAT exam, as shown in column (1) of Table 1. Students in the marginal sample performed relatively worse on the SAT exam with an average score of 1163, 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 fo,r marginal students. Students in the marginal sample are more likely to be required to take remedial Math (5 percent) and English (13 percent) courses upon enrollment. The ratio of Pell Grant eligible students is low for both samples, but slightly higher

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.

for the marginal one (15 percent). Additionally, students in the marginal sample are 2 percentage points more likely to have an expected family contribution of less than $30,000 and thus more likely to qualify for federal student loan assistance. While the proportion of educated parents are quite high at this university—roughly 80 percent—parents of students in the marginal sample tend to be slightly less educated.

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 dropout after 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 measured labor market outcomes at the ages 28 to 33. The choice of starting at age 28 is because early lifetime earnings are known to be noisy and volatile. Additionally, we cannot measure earnings passed the age of 33 given that the oldest cohort in our sample entered university in 2007 and we can measure earnings up until the last quarter of 2022. Using these data, we find that, for the full sample, 67% of quarters have students observed in the labor market between the ages of 28 to 33. This number is slightly larger (69 percent) for marginal students. We also report mean quarterly earnings of 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 we study. Specifically, students 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 documented impacts on future outcomes to be the causal effect of being placed on academic probation. Formally, we estimate the following reduced form equation:

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

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 throughout.[3] 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. The preferred specifications in this paper 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 their unobserved determinants of the 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 to four courses taken during the quarter making it highly unlikely to be precisely controlled. Nonetheless, we conduct a series of empirical checks and exercises to alleviate any concerns that unobserved at-

3. The university has a total of six colleges or faculties.

tributes of students just above and just below the cutoff may 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 should 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 also 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 indicates that while these distributional discontinuities could be the result of strategic sorting, they could also simply be because the number of combinations that result in whole-number GPAs are larger than those for decimal GPAs, especially after only one quarter. While, the first case is obviously problematic, the latter poses little to no threat to identification and is consistent with findings from 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 characteristics and predetermined outcomes. 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 after 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 may 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 bandwidths chosen from the CCT optimal bandwidth selector, we present estimates over 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

4. Throughout our analysis we exclude first-quarter (Q1) GPA when looking at first-year GPA as an outcome. We do so because our running variable is based on Q1 GPA. Additionally, we focus on first year GPA since there is little attrition during first year relative to later years and, as such, these provide for the cleanest GPA estimates.

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 the ages of 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, Hurwitz and Howell, 2013). We therefore next examine heterogeneous effects by student 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 presented 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 signif-

5. The choice of starting at age 28 is because early lifetime earnings are known to be noisy and volatile (Hoekstra, 2009). Additionally, we cannot measure earnings passed the age of 33 given that the oldest cohort in our sample entered university in 2007 and we can measure earnings up until the last quarter of 2022. As a robustness check, we later report estimates from specifications where we define labor market outcomes at 25 to 55 quarters after university enrollment and the results remain unchanged.

icant. 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 suggest 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 look at 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, we move beyond looking at labor market outcomes at a fixed age range and instead re-conduct our main analysis looking at 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

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

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).

Appendix Table A5 and remain very similar to our main specification.

Finally, 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 from 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.

6 Discussion and Conclusion

This paper documents a substantial graduation and wage penalty for students placed on academic probation, particularly for those from low-income families. To better understand why, we examine the timing of the probation-induced attrition, two additional contemporaneous outcomes—a proxy for financial aid eligibility and major switching, and 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 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 earning 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

8. We also conduct this 'Donut' analysis for our alternative specification looking at labor market outcomes 25 to 55 quarters after university enrollment. These results are summarized in Appendix Table A7.

financial aid if their cumulative GPA at the end of their first year is below a 2.0 (University Policy Link for Financial Aid Eligibility). 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'. 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 examine the evolution of wage differences between students exposed to probation relative to those not exposed. To do this, we utilize the richness of our linked administrative data and obtain a series of RD estimates for wages one year from entry up to 12 years. Figure A5a plots these estimates. The first estimate plotted in this figure corresponds to differences in logged earnings during the first year of university entry between students just below the threshold (treated groups) and those just above (control groups). We detect no meaningful differences between treatment and control groups during the first year. This is unsurprising, given that we find probation-induced dropout doesn't begin until the end of year one. That is, during year one, both treatment and control groups are still full-time students. However, the RD estimates show a divergence in wages during the second year from entry. Students exposed to early probation earn about 20 percent more than those who narrowly missed the probation label, though this difference is not statistically significant at conventional levels. We interpret this as marginal students who are exposed to probation —and who were more likely to dropout following the first year—experience a transitional period of higher earnings, relative to those who are retained and not exposed to probation. However, this difference is short-lived as there is a rapid shift back to comparable earnings between the two groups in years three through five post entry. This pattern provides evidence against a proposed counterfactual channel in which students, who just qualify for probation and drop out, are permanently entering the labor market in non-degree type jobs. This pattern reverses in the long-run as we observe that probation students earn less than students not on probation in years 5 through 12 from entry; though these estimates never attain significance at conventional levels.

When we narrow in on low-income students, the group most impacted by probation, the evolution of wages is consistent with the full sample, but is much more striking. Figure A5b reports these results and reveals that low-income students exposed to probation earn up to 40% more than their counterparts, who are not exposed, in the second year fol-

lowing university entry. However, these differences quickly start to fade and are negative and significant starting in year five, and for most subsequent years. As such, our findings indicate that low-income students on probation earn approximately 40 to 50 percent less than low-income students not exposed to probation in years 5 through 12 following entry. Importantly, we find no such patterns in the data when looking at high-income students (A5c). In summary, we take this as evidence that low-income students who experience probation-induced dropout at the end of year one, temporarily enter the labor market, then most likely enroll in a less selective four-year institution or a two-year college which yields much lower earnings than their counterpart by age 30 when wages start to stabilize.

We glean at least four insights from these additional analyses. First, probation-induced dropout occurs rather immediately; for the most part it occurs at the end of year one. Second, differences in major switching behavior between low- and high-income students are unlikely to explain our main results. Third, given the statistically insignificant results documented in column (1) of Table A9, we speculate that the main driver of the disparate attrition results is more likely linked to to non-financial barriers such as access to information, support, encouragement, etc,...[9] This is consistent with a large recent literature showing that non-financial barriers are a huge obstacle for low income students (See Dynarski et al., 2023 for a review). Fourth, for low-income students, the earnings penalty of probation emerges once the untreated students (who were retained) are entering the labor market for the first time with their degree, suggesting that the treated students who were induced to dropout likely go on to attend and graduate from less selective institutions that have lower average earnings.[10]

In conclusion, findings from this paper indicate that the probation policy carries a large, and previously undocumented, short and long-run penalty for students. This burden disproportionately impacts low-income students who are more likely to dropout when exposed to probation as compared to their high-income counterparts. This substantially impacts their career earnings which do not seem to recover many years after entry.

9. We caveat this interpretation by noting that the results presented in column (1) Table A9 are quite imprecise, and large in magnitude, precluding us from making any definitive conclusions.

10. 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.

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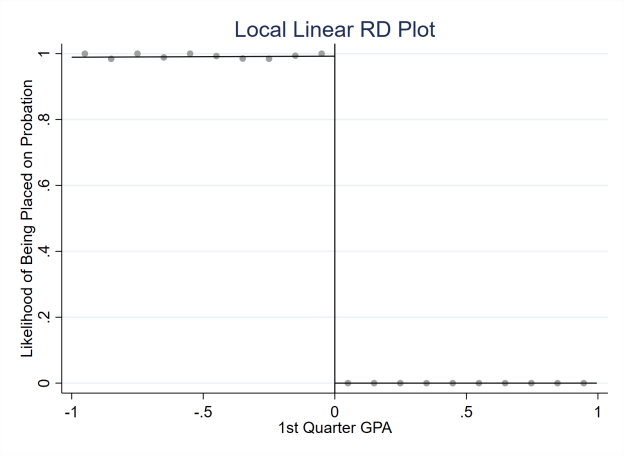
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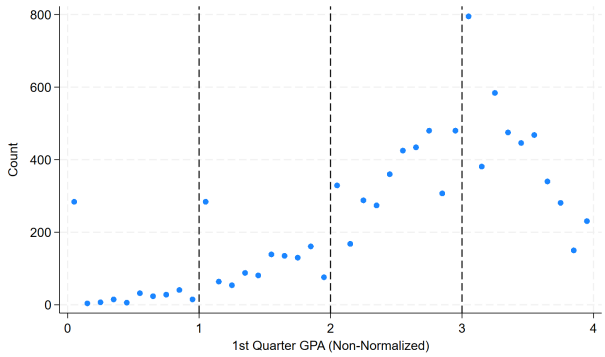
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A Figures

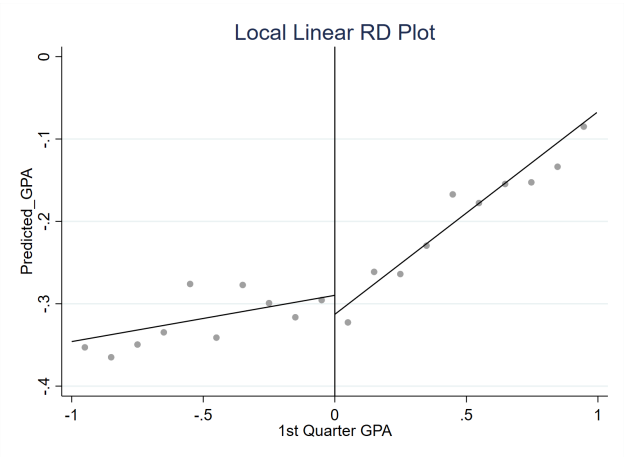
Figure 1: Probation Policy in Practice



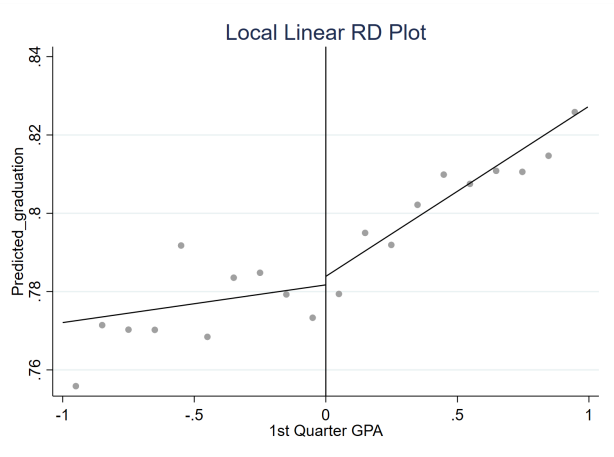
(a) Likelihood of Being Placed on Probation



(b) Distribution of Q1 GPA



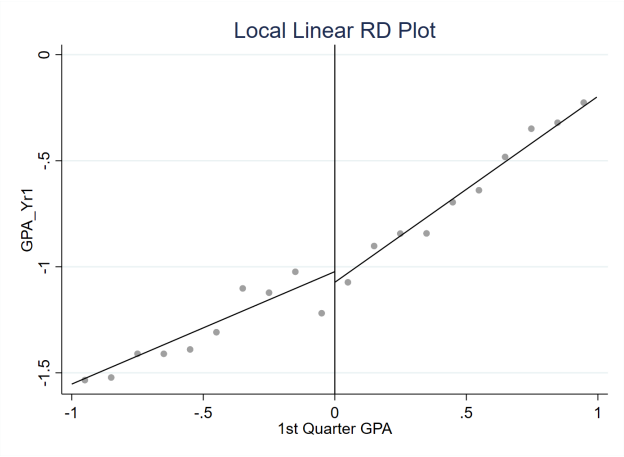
(c) Predicted 1st Year GPA



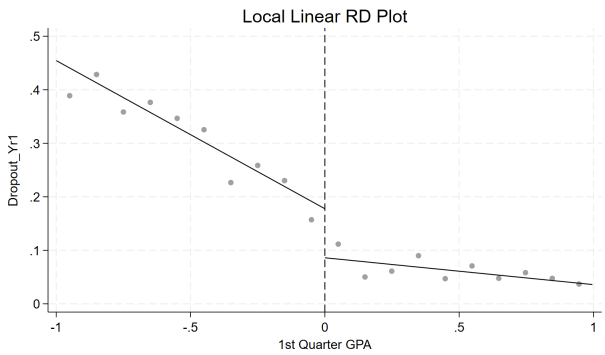
(d) Predicted Graduation Rates

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.

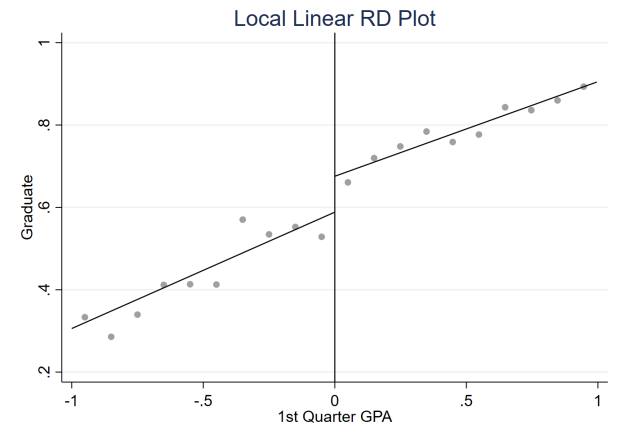
Figure 2: Visual RD Evidence on Academic and Labor Market outcomes



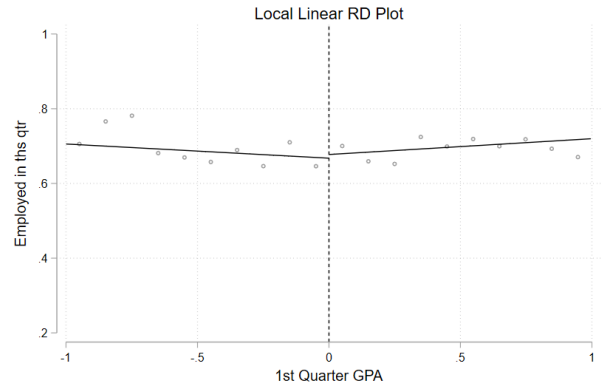
(a) Q2+Q3 GPA



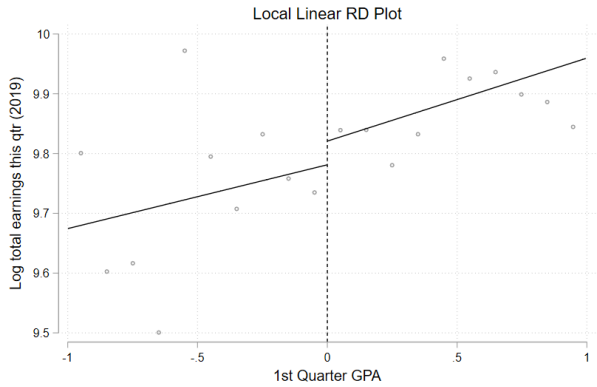
(b) First-Year Dropout



(c) Six-year Graduation Rates



(d) Likelihood of Employment



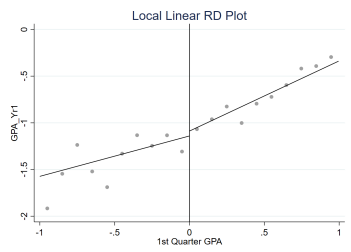
(e) Log Earnings

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 the ages of 28 to 33. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

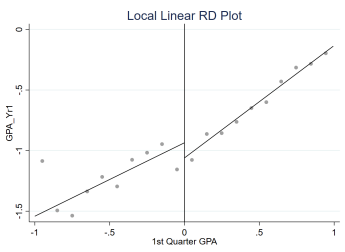
Figure 3: Visual RD Evidence for Main Outcomes Based on Income Status

Low-Income

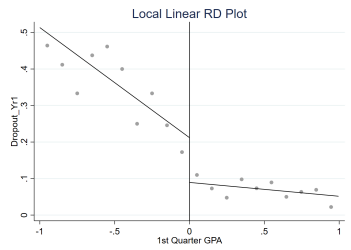
High-Income



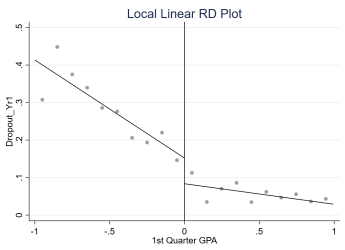
(a) Q2+Q3 GPA



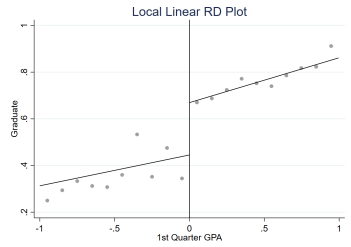
(b) Q2+Q3 GPA



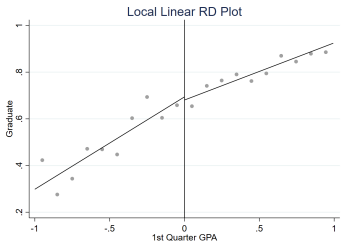
(c) First-Year Dropout



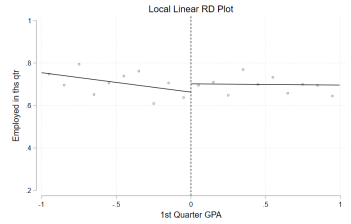
(d) First-Year Dropout



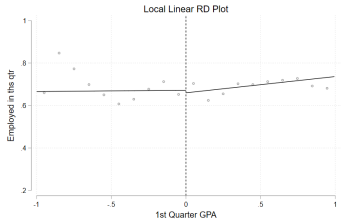
(e) Six-year Graduation Rates



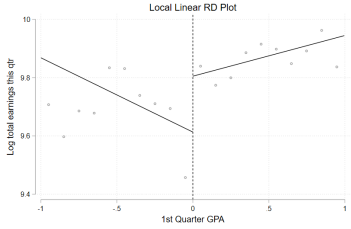
(f) Six-year Graduation Rates



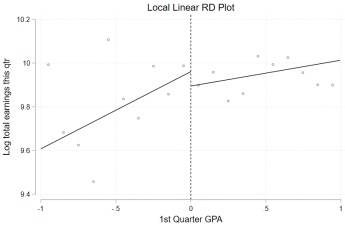
(g) Likelihood of Employment



(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 above. 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 the ages of 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.

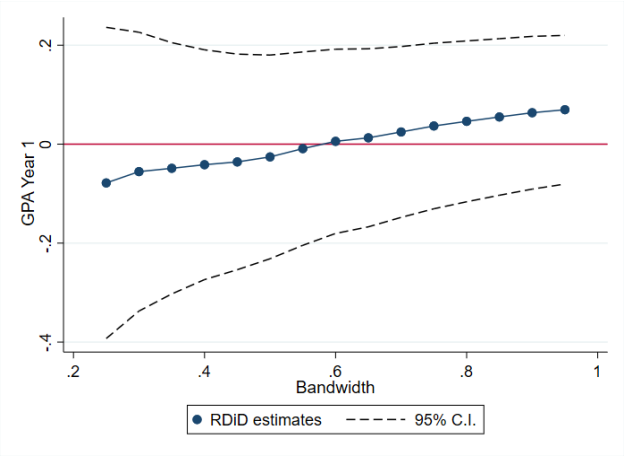
Table 2: RD Estimates of Probation on Academic and Labor Market Outcomes

	GPA (Q2+Q3)	**Year-1 Dropout**	**6-year Graduation**	**Employed**	**Log Earnings**
	(1)	(2)	(3)	(4)	(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

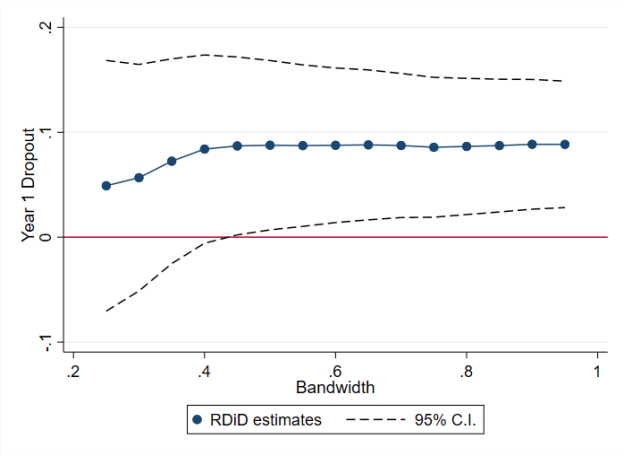
Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Low-income students are those with an Expected Family Contribution of less than $30,000 while high-income students are those above Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. Local linear RD regressions using a triangular kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty 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 reported in parentheses in columns (1), (2) and (3). Clustered standard errors (at individual level) reported in parentheses in columns (4) and (5).*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C Appendix Figures

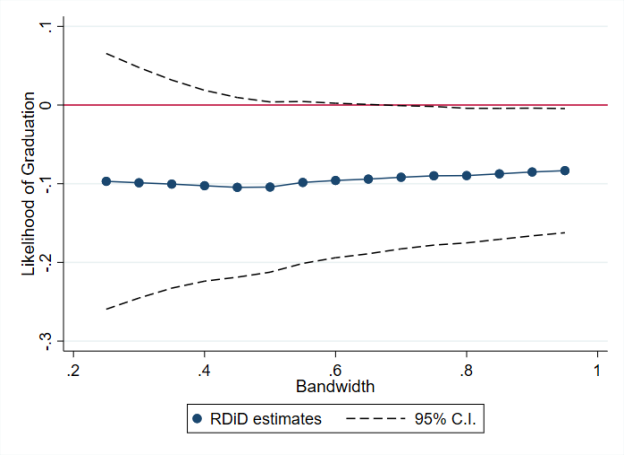
Figure A1: Robustness of Bandwidth Choice for Academic and Labor Market outcomes



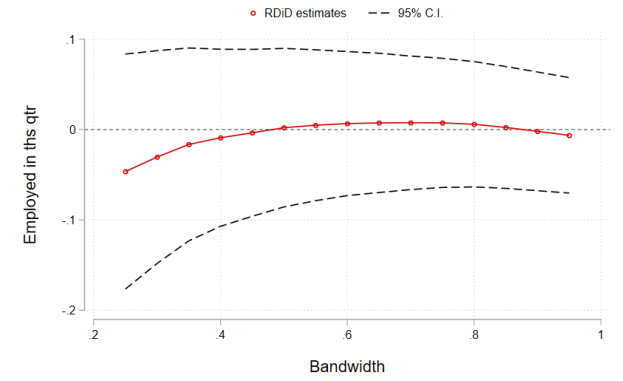
(a) Q2+Q3 GPA



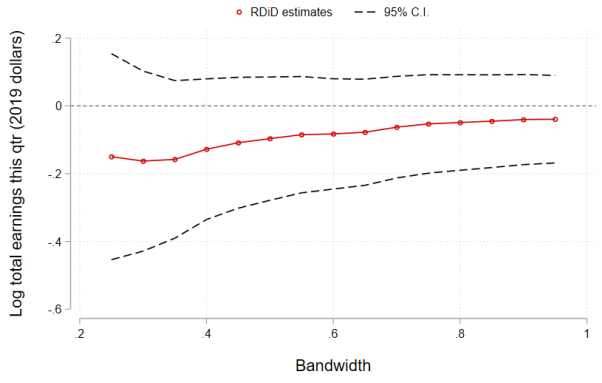
(b) First-Year Dropout



(c) Six-year Graduation Rates



(d) Likelihood of Employment

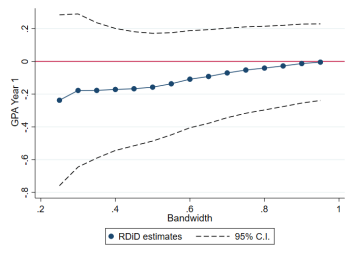


(e) Log Earnings

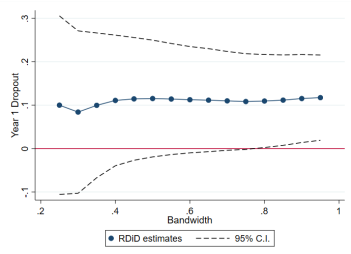
Notes: The sample includes all first-time freshmen enrolled at the university in entering fall cohorts 2007, 2008 and 2009 (select faculties). Scatter points represent estimates from local linear regressions ranging from 0.25 to 1 GPA point on either side of cutoff. Upper and lower 95% confidence intervals reported using dashed lines. GPA is standardized by cohort and reported for all students. Figures in panels (d) and (e) are based on stacked labor market outcomes at the ages of 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

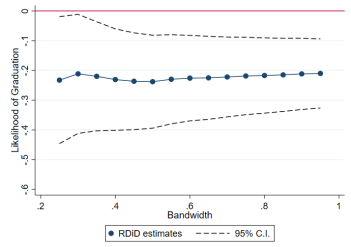
Low-Income



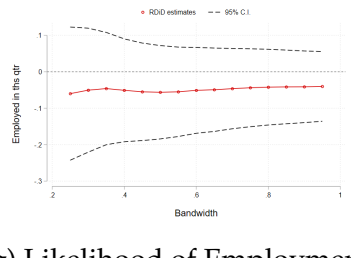
(a) Q2+Q3 GPA



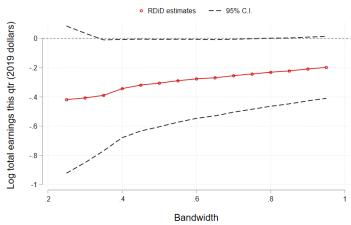
(c) First-Year Dropout



(e) Six-year Graduation Rates

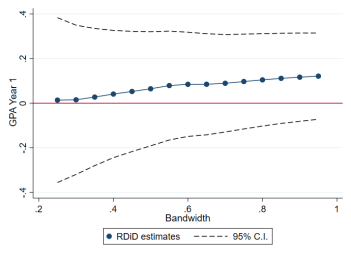


(g) Likelihood of Employment

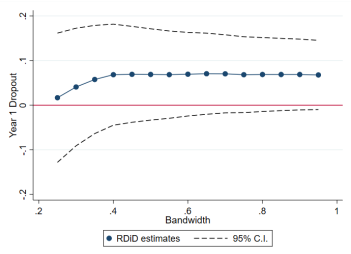


(i) Log Earnings

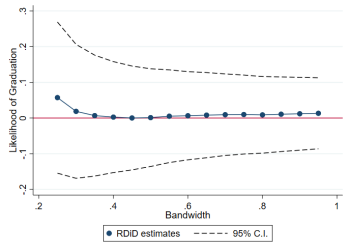
High-Income



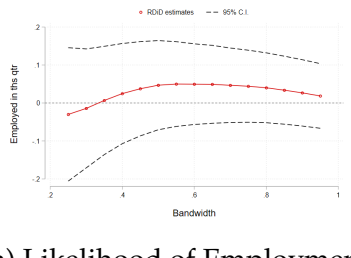
(b) Q2+Q3 GPA



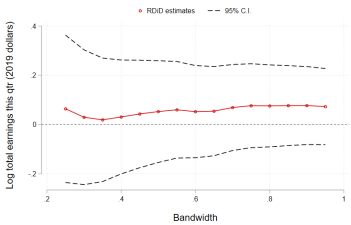
(d) First-Year Dropout



(f) Six-year Graduation Rates



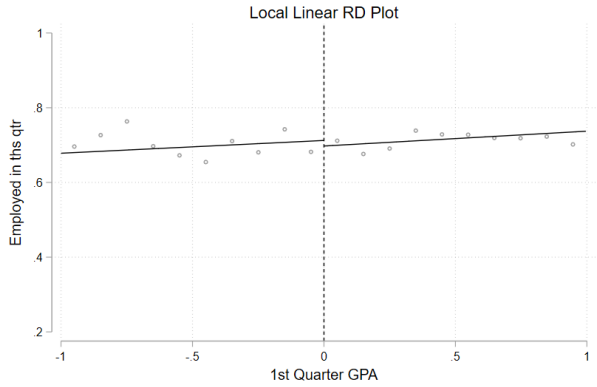
(h) Likelihood of Employment



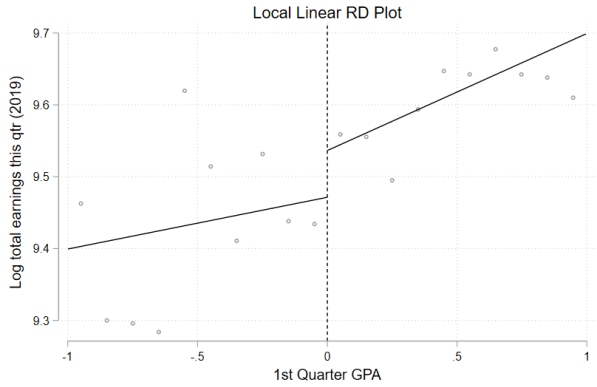
(j) Log Earnings

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 above. Scatter points represent estimates from local linear regressions ranging from 0.25 to 1 GPA point on either side of cutoff. Upper and lower 95% confidence intervals reported using dashed lines. GPA is standardized by cohort and reported for all students. Figures in panels (g) through (j) are based on stacked labor market outcomes at the ages of 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



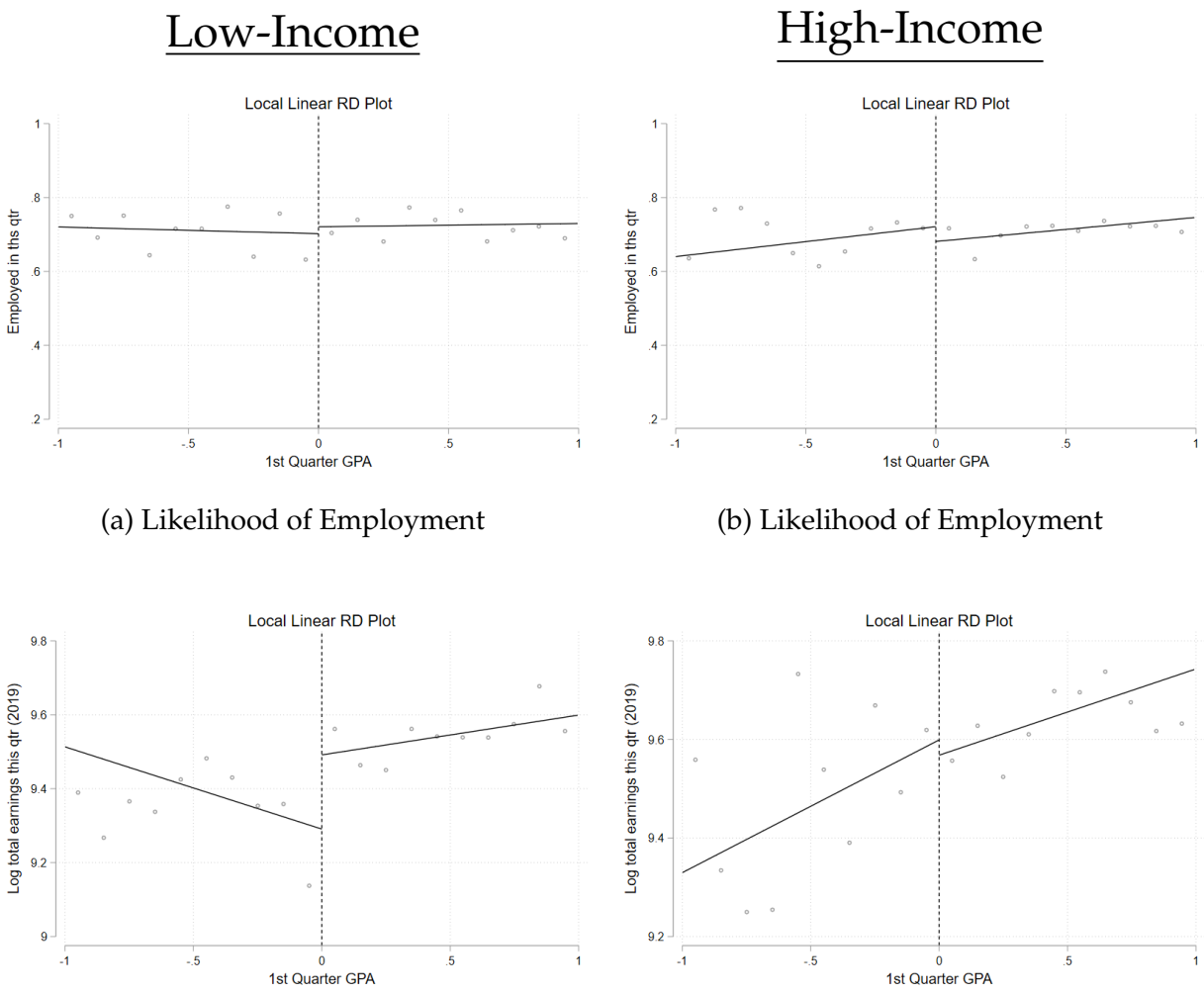
(a) Likelihood of Employment



(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 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 after University Enrollment



(a) Likelihood of Employment

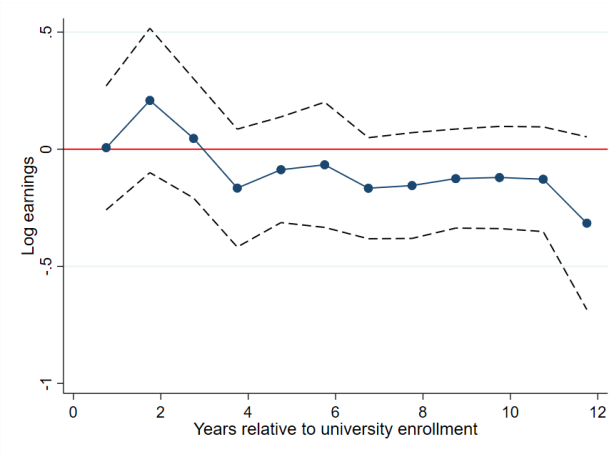
(b) Likelihood of Employment

(c) Log Earnings

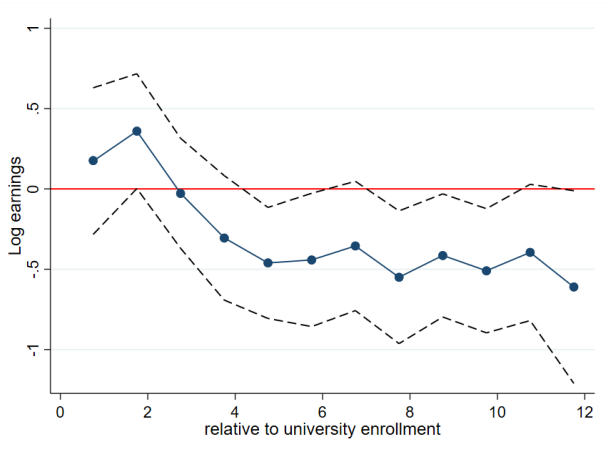
(d) Log Earnings

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 above. 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 after university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers.

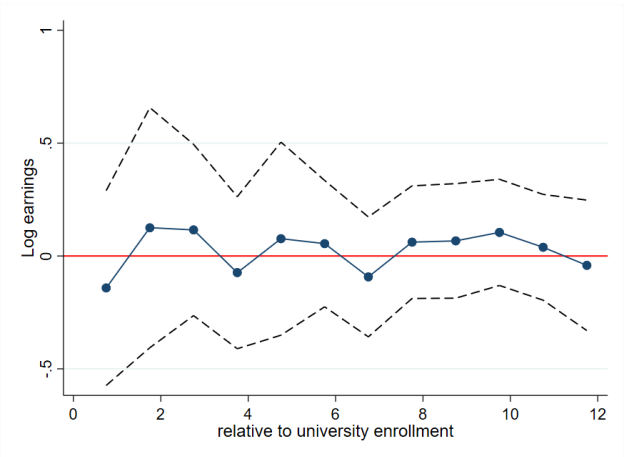
Figure A5: RD wage estimates relative to university enrollment year



(a) All students



(b) Low-income students



(c) High-income students

Notes: 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 above Scatter points represent RD estimates on the effects of probation on log earnings relative to university year enrollment. Dashed lines represent uppper 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 faculty fixed effects. Local linear RD regressions using a triangular or uniform kernel function reported throughout. Robust standard errors 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 above. Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. Local linear RD regressions using a triangular kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty 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) 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 above. Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. Local linear RD regressions using a triangular kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty 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) 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)	**Year-1 Dropout**	**6-year Graduation**	**Employed**	**Log Earnings**
	(1)	(2)	(3)	(4)	(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 above. Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. Local linear RD regressions using a uniform kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty 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) reported in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: RD Labor Market Effects of Probation 25 to 55 Quarters After 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 above. Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. Local linear RD regressions using a triangular kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty fixed effects. Labor Market outcomes are stacked and reported 25 to 55 quarters after university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors (at individual level) 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 above. 'Donut' regressions involve dropping observations at 1.9 and 2.0 exact GPA points. Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. Local linear RD regressions using a triangular kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty 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 reported in parentheses in columns (1), (2) and (3). Clustered standard errors (at individual level) 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 After 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 above. 'Donut' regressions involve dropping observations at 1.9 and 2.0 exact GPA points. Each point estimate is from a separate regression. CCT bandwidth selector used to select optimal bandwidths for each regression. "Donut" local linear RD regressions using a triangular kernel function reported throughout. All regressions include controls for gender, race and parents' education as well as cohort and faculty fixed effects. Labor Market outcomes are stacked and reported 25 to 55 quarters after university enrollment. Earnings have been adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Clustered standard errors (at individual level) 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 above. All regressions include controls for gender, race and parents' education as well as cohort and faculty fixed effects. CCT bandwidth selector used to select optimal bandwidths for each regression. All regressions use a triangular kernel. Robust standard errors reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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 above. All regressions include controls for gender, race and parents' education as well as cohort and faculty fixed effects. CCT bandwidth selector used to select optimal bandwidths for each regression. All regressions use a triangular kernel. Robust standard errors reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.