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The pitfalls of higher selectivity: Evidence on university degree completion *

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Abstract

We study the effect of selectivity on university degree completion. Using data from the centralized university admission system in Chile, which includes students' ranked options, we use a regression discontinuity design with students at the margin of admission between relatively more and less selective university programs. We find that students marginally admitted to a more selective program are 2.3 percentage points less likely to graduate from their initial program, compared to marginally rejected students who were instead admitted to the relatively less selective option. We also find a 1.9 percentage point drop in the likelihood of obtaining any university degree. For students who graduate, we find a one-month increase in time to graduation. This decline in overall graduation rates is driven by lower-income students, who face greater challenges in transferring and completing a degree elsewhere. We find suggestive evidence that these results are driven by higher academic rigor, rather than by ordinal rank.

JEL Classifications: I23, I24, I31, J24

Keywords: university, selectivity, degree completion, inequality

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1 Introduction

There is a large body of evidence showing positive returns to higher education. But not everyone who goes to college ends up graduating. According to the OECD, 12% of students who enter a bachelor program leave before the second year, and only 39% of full-time students graduate within the planned duration of their bachelor program (OECD, 2022). Given the significant resources students spend during their university years on tuition and foregone earnings, along with the substantial funding provided by governments and universities, understanding the determinants of degree completion is essential to minimize potential inefficiencies caused by student dropouts.

A factor potentially influencing degree completion is program selectivity. Studying at a more selective university provides students access to a higher-quality education, including more qualified faculty and enhanced support services. Additionally, students enrolled in more selective programs will have a more academically capable peer group, potentially creating positive learning externalities. Both of these factors could improve students' educational experience and result in higher degree completion. However, increased selectivity often comes with greater academic rigor, which may place additional pressure on students, and could result in lower rates of degree completion. Moreover, students surrounded by more able peers might experience negative effects if such peer interactions lower their self-perception. As a result, the net effect of selectivity on degree attainment remains theoretically ambiguous.

In this paper, we examine the effect of program selectivity on university degree completion. We study this question in the context of Chile's centralized university admission system, using administrative data from the 2007-2015 application cycles. We use a regression discontinuity (RD) design, focusing on applicants close to the admission threshold for a university program (i.e., a major within a given university). A key advantage of the Chilean system is that it allows us to identify the program each applicant would be admitted to if marginally denied admission to a more preferred option—their next-choice, or fallback program. This type of counterfactual is rarely observed directly in studies of college selectivity, where researchers often cannot distinguish whether a marginally rejected student's fallback option is attending a less selective university program, a non-university program, or no postsecondary education at all. We take advantage of this feature, and restrict our sample to cases in which the student's fallback option is a considerably less selective university degree.[1] Additionally, we limit our sample to students who are above the

[1]We measure program selectivity using the median math and language test scores of admitted students. Importantly, it is common for students in the Chilean context to be at the margin of admission between two programs with different levels of selectivity, providing the identifying variation necessary to study this

admission threshold in their fallback option. This ensures that the counterfactual option is admission to a relatively less selective university program, rather than non-admission to any university within the centralized system.[2] Without this restriction, being marginally admitted to the more selective program would mechanically result in higher graduation rates. Another advantage of the Chilean context is that the admission system creates admission discontinuities for programs across the selectivity distribution. This allows us to examine this question for programs of different selectivity and university students with varying ability levels.

We find that students marginally admitted to a more selective program are 2.3 percentage points *less* likely to graduate from the first program they enroll in, compared to those admitted to their relatively less selective fallback program (a 4.8% decrease). Furthermore, we find an average increase of one month in time to completion for students who do graduate. Importantly, our results are not driven by differences in the field of study at the cutoff. We also find that this 2.3 percentage point increase in dropout rates is matched by an almost equivalent rise in the likelihood of enrolling in another university program, with most of these marginal dropouts enrolling in programs that are relatively less selective. However, we do not find a statistically significant increase in the likelihood of graduating from another program. Overall, we find that students marginally admitted to a relatively more selective program are 1.9 percentage points less likely to obtain any university degree. This decline in overall graduation rates is driven by students from lower-income households and lower-ability students, who face greater challenges in transferring and completing a degree elsewhere. Finally, we find similar effects for relatively more and less selective programs.

There are different potential mechanisms through which crossing the admission threshold for a more selective program may result in lower graduation rates from the first program students enroll in. On the one hand, more selective programs typically have higher academic rigor. This may reflect a more demanding curricula, or the fact that instructors adapt their teaching and evaluations to higher-ability students (de Roux and Riehl, 2022). Consequently, students at the margin may find it harder to meet program requirements, resulting in lower graduation rates. On the other hand, students marginally admitted to more selective programs have a significantly lower ordinal rank, potentially affecting their self-concept, perceived comparative advantage, and expectations (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020). To examine the role of ordinal rank,

question.

[2]As a result, our approach necessarily excludes students at the lower end of the ability distribution who are on the margin between being admitted to a university program and not being admitted anywhere.

we conduct a placebo estimation with applicants at the margin of admission between two programs with similar selectivity levels. Importantly, students who are marginally admitted to the more preferred of the two programs will experience a sizable drop in rank, with negligible differences in academic rigor and peer ability. We do not find a negative effect on graduation outcomes, indicating that the our results are not driven by ordinal rank. These results suggest that the negative effects of selectivity that we uncover are driven by higher academic rigor.

Our paper relates to the literature examining the effect of college selectivity on degree completion.[3] Several studies in this literature, primarily from the U.S., use RD designs to examine the impacts of attending more selective 4-year colleges, often focusing on a specific institution or group of students. Unlike our paper, most of these studies find that enrolling in a relatively more selective college *increases* the likelihood of obtaining a bachelor's degree for students at the margin of admission.[4] In some of these studies, students' fallback option is a 2-year college or not enrolling at all (Zimmerman, 2014; Goodman et al., 2017), or another 4- or 2-year college (Mountjoy, 2026), making the increased likelihood of earning a bachelor's degree at the cutoff at least partly mechanical.[5] Also in the U.S., Cohodes and Goodman (2014) focus on students who are at the margin of attending 4-year colleges with different levels of selectivity. The authors find that high school graduates in the top 25% of Massachusetts are less likely to obtain a university degree if they attend lower-quality in-state public colleges, compared to higher-quality in-state private or out-of-state colleges. An important distinction is that students in the U.S. apply to college without needing to choose a major beforehand. In contrast, in most other countries, students apply directly to specific programs that combine a university and a major, and switching majors is considerably more difficult than in the U.S. (Bordon and Fu, 2015; Lovenheim and Smith, 2023). A possible explanation for why our findings differ from Cohodes and Goodman (2014) is that struggling students in contexts like Chile

[3] Many studies focus on the effects of selectivity on future income, finding positive effects (Hoekstra, 2009; Zimmerman, 2019; Anelli, 2020; Sekhri, 2020). Most of these studies also provide evidence on the effects on degree completion.

[4] Other studies examining this question using cross-sectional regressions that control for predetermined characteristics find positive average effects of selectivity on degree completion (e.g., Bound, Lovenheim and Turner, 2010 and Dillon and Smith, 2020), although there is mixed evidence on whether low ability students benefit from higher selectivity (Loury and Garman, 1995; Light and Strayer, 2000). See Arcidiacono and Lovenheim (2016) and Lovenheim and Smith (2023) for a review.

[5] A similar issue arises with studies examining the effect of affirmative action or top N programs (Bleemer, 2022; Tincani, Kosse and Miglino, 2023; Barahona, Dobbin and Otero, 2023; Black, Denning and Rothstein, 2023). Although these papers typically find that students from underrepresented minorities are more likely to earn a degree when they enroll in more selective programs, the counterfactual for many of these students is attending a 2-year college or not enrolling at all.

have less flexibility to adjust before having to drop out.[6]

Outside of the U.S., a few papers study the effects of selectivity for higher-ability students in specific fields of study. Anelli (2020) finds that marginal admission to an elite university in Italy offering business, law and economics degrees increases the likelihood of obtaining a university degree from any university in that city. However, it is unclear whether these findings would still hold when considering university degree completion from universities in other cities. Also in Chile, Zimmerman (2019) finds that marginal admission to elite business-focused programs has small or zero effects on the likelihood of obtaining any university degree. We build on these studies by examining a wider range of academic programs and considering students across different ability levels, offering a more comprehensive perspective on the relationship between selectivity and degree completion.

Our contribution to the literature is threefold. First, since we can observe students' fallback option, we are able to focus on students for whom the counterfactual is admission to a relatively less selective university program, thus minimizing the risk that our findings are mechanically driven by changes in the likelihood of attending university. Second, we study the effect of selectivity in a context where the structure of higher education differs significantly from that in the U.S. in terms of the barriers to switching majors. These differences could influence how selectivity impacts degree completion. Third, we provide evidence on the effect of selectivity for a broad set of programs and consider students across a wide range of ability levels.

The rest of the paper is organized as follows. Section 2 presents information on the Chilean context, and Section 3 explains our data and estimation strategy. Section 4 presents the main results and validity checks, Section 5 analyzes the mechanisms, and Section 6 concludes.

2 Higher education in Chile

Tertiary education in Chile comprises universities offering bachelor degrees, usually lasting four to six years, and technical institutions offering technical or vocational degrees. In 2007-2015, 61% of post-secondary enrollment was at a university. At the beginning of our analysis period, all public universities (25 state and non-state institutions) participated

[6]Evidence from the U.S. shows that students respond to information about academic fit by changing majors, often moving away from more demanding or more harshly graded fields (Zafar, 2011; Arcidiacono et al., 2012). In contrast, in Chile (as in many other countries), students have to repeat the university application process in order to switch majors, with no guarantee that they will be able to transfer their credits or financial aid to the new program (see Section 2 for more details).

in a centralized admission system (*Sistema Único de Admisión*, or SUA), while no private universities were included. In 2013, the SUA started admitting private universities, with eight joining that year.[7] To participate in this system, universities must be non-profit. In 2007-2015, 56% of university enrollment was at a university participating in the SUA.

Applicants to the SUA must take a standardized test called *Prueba de Selección Universitaria* (PSU), which is held at the end of each school year. The PSU covers four subjects: mathematics, reading, history and social sciences, and natural sciences. The former two are mandatory, and students must take at least one of the latter two. Each subject test score is standardized with a mean of 500, a standard deviation of 110, and a range of 150 to 850. Students' high school GPA and, since 2012, their within-school GPA rank are also mandatory inputs that are standardized using the same scale. Since 2010, PSU scores are valid for two years instead of just one.

After receiving their PSU scores, along with their high school GPA and ranking, applicants to SUA universities submit their applications through an online platform. Students rank their preferences (up to eight before 2011 and ten from 2012 onward), which are a combination of major, university, and campus (e.g., law in the Santiago campus of *Pontificia Universidad Católica*). We refer to this as a program. For each program, universities set the ex-ante weights for each PSU subject, high school GPA, and ranking and determine the number of vacancies offered. This implies that students might have different weighted scores for various programs in their lists. After students submit their preferences, the system implements a deferred acceptance algorithm using their preferences, weighted scores, and available seats. Once the available seats in a program are filled, applicants with scores below that of the last admitted student are placed on a waitlist. In a second round, seats declined by admitted applicants are assigned to waitlisted applicants in order of merit. Given this application process, cutoff scores vary from year to year, creating uncertainty about students' ability to predict their acceptance into a specific program.

Applicants can also apply to universities outside the SUA by submitting their applications directly to each institution, which have independent application processes. Therefore, a student can be admitted into an SUA program and one or more non-SUA programs.

During our analysis period, universities charged tuition to all their students. For example, in the 2010/11 academic year, the average annual tuition at public institutions was USD $5,885 (PPP) (OECD, 2014). However, financial aid was available to many students: 68% of those attending public institutions benefited from public loans and/or

[7] As of 2024, there were 58 universities (of which 45 participate in the centralized system), and 79 technical institutions.

scholarships. The government provided most of the financial aid, with students applying for funding several months before the university admission process. Access to these scholarships and loans depended on both academic performance and economic need.[8] Financial aid covers the reference tuition fee, which is roughly 80% of the full tuition fee (Barrios-Fernández, 2022).[9] Students must cover the difference and maintenance costs since these are not included. These grants or loans can be used for a limited number of years, depending on the formal length of the program.[10]

Programs are structured such that students have to complete a fixed curriculum, with very few (if any) credits coming from electives or modules from other departments. If a student decides to change their major, even within the same university, they are usually required to retake the PSU, apply through the SUA system, and request credit transfers to the new program. This process may result in no credits being transferred, forcing the student to start from the first year. Additionally, students must apply to transfer their financial aid to the new program.

SUA university programs are mainly full-time, with classes during the daytime shift. Part-time or evening programs are more common in the non-university post-secondary sector, in some private universities, or during postgraduate degrees. Only 4.4% of the regular SUA enrollment in 2007-2015 corresponds to evening, online, or hybrid arrangements.

3 Data and estimation strategy

3.1 Data and sample

We rely on two main sources of data. The first is data from the SUA admission process in 2007-2015.[11] For each applicant, we observe the PSU score in each subject, their high school outcomes (GPA and within-school ranking), and several sociodemographic characteristics provided by the student at the time of application, such as their family income or parents' educational level. For each program the student applied to, we have information on

[8] The two main government-backed student loan programs, the *Fondo Solidario de Crédito Universitario* (FSCU) and the *Crédito con Aval del Estado* (CAE), required applicants to meet a minimum average PSU score in math and language. These programs largely excluded students in the highest income brackets. Government scholarships applied similar but more stringent criteria (Barrios-Fernández, 2022).

[9] Since universities can freely determine their tuition fees, the government sets reference tuition fees for each program to control expenditure.

[10] Currently, the CAE can be used for up to three extra years. The FSCU allows for an extra 50% on top of the nominal length of the program.

[11] Cohorts are named by their starting year, not the application year. For instance, the 2007 cohort took the PSU at the end of 2006 to start college in March of 2007.

the preference order, the applicant's admission score, and the first-round outcome. Our second data source is enrollment and degree completion records in all tertiary education programs from 2007 to 2023. This includes not only SUA programs but all other programs in higher education, allowing us to analyze whether students enroll in and complete any higher education degree in the country. Each dataset has unique student identifiers, allowing us to merge the two datasets and track students across time.

To estimate the causal effect of admission to a relatively more selective program using a regression discontinuity design, we focus on applicants to the centralized admission process at the margin of admission between a more and less selective program. We then use the distance to the admission score cutoff for the most preferred of these two programs as the running variable. We measure the selectivity of all programs in the SUA system using the median of the average math and reading PSU scores of students admitted in the first round, converted into percentiles.[12]

We focus on first-time applicants to the centralized admission process in 2007-2015.[13] We start our analysis in 2007 because the enrollment data from previous years does not include programs outside the centralized admission system. We limit the final cohort to 2015 to ensure sufficient time for students to complete their degrees (9 years). As we are looking to compare students marginally admitted to a more vs. less selective program, we exclude students who were not offered any spot in the first round (29% of applicants). Furthermore, as we analyze graduation rates conditional on enrollment, we exclude students who did not enroll in any university degree within three years of applying through the SUA (4.8% of those offered a first-round spot).[14] We also drop students who applied to programs with an additional entry exam (usually theater or music), as we do not have data on the results of these assessments.

We focus on applications to oversubscribed programs in which the student was admitted or waitlisted in the first round (what we refer to as a target program). For each target program, we identify the student's fallback option. The fallback is the program they would get into if narrowly denied admission to the target program; it is the most

[12] We use weights for the number of admitted students so that each percentile has the same number of people. Alternatively, one could measure selectivity using the last admitted student's math and reading PSU scores. However, these two measures are strongly correlated (0.96 correlation).

[13] We define first-time applicants as individuals whose first observed application from 2004 onward was in 2007-2015. Since the data on SUA applications only starts in 2004, some individuals may have applied prior to this year without being captured in our dataset.

[14] We exclude these students because many of the outcomes we study, such as dropout rates and transfers, are not defined for students who do not enroll in university. By excluding these students, we restrict the analysis to university outcomes of university students. Importantly, we also show results on the likelihood of graduating from any university program for the entire sample, regardless of whether they enroll in university or not, and find similar results (see Section 4).

preferred option among programs that are less preferred and less selective (from the student's perspective) than the target, and where the student's application score is above the cutoff. Similar to Aguirre, Matta and Montoya (2024), we drop observations from target programs for which there is a higher-ranked option that is relatively less selective from the student's perspective.[15] We make this restriction because, in such cases, even if the student's admission score for this program exceeded the cutoff, they would never enroll there, as they would have already been admitted to a more preferred option. We use observations in which the applicant has been admitted to either the target or fallback program in the first round. Finally, we drop cases in which either the target or fallback belongs to a *Bachillerato* program (8.7% of cases)—two-year programs offered by universities for students who want to explore different academic fields before applying to a bachelor's degree.

Panel A of Appendix Figure A.1 plots the distribution of selectivity differences between target and fallback programs. Since we are interested in estimating the effect of selectivity, we exclude observations with minimal variation in program selectivity; in particular, we restrict our sample to target programs with at least a 10 percentile point difference in selectivity with the student's fallback (62% of cases). We examine the sensitivity of our estimates to changes in this sample restriction in Section 4.2. We also drop the few observations for which the fallback program is more selective than the target program.[16] Panel B of Appendix Figure A.1 plots the selectivity distribution of the target programs in our final sample. These university programs span the selectivity distribution within the SUA system, although, by construction, they are at or above the 10$^{\text{th}}$ percentile.

Our sample has 271,883 observations, corresponding to 241,488 students. Students can appear more than once in our sample if they have multiple target programs satisfying the specified conditions.[17] Table 1 presents descriptive statistics for the students in our sample (column 1), and compares these students to the larger sample without restrictions in the selectivity difference between target and fallback (column 2). The students in our sample are less likely to live in the Metropolitan region (which includes Santiago) than the students in the unrestricted sample (30.4% vs. 35.1%), and are of slightly lower

[15]We calculate relative selectivity as the distance between the last admitted student's score and the student's weighted score.

[16]In these cases, although the target program is more selective than the fallback from the student's perspective (i.e., using the program's admission score), it is less selective using our selectivity measure (median math and language PSU scores).

[17]For instance, a student admitted to their second-choice program, where there is at least a 10-percentile point difference in selectivity between their first and second choice as well as between their second and third choice, will appear in our sample twice: once with an observation where the first program is the target (and the second is the fallback) and another where the second program is the target (and the third is the fallback).

socioeconomic status (e.g., only 15.9% went to a private high school, vs. 20.7% in the broader sample). Appendix Table A.2 compares the main characteristics of the target and fallback programs in both samples. The average selectivity difference between the target and fallback programs in our sample is nearly 25 percentile points. On average, the target programs are ranked at position 1.73, whereas the fallback programs are ranked at 3.28. The programs in our sample are spread across different fields of study, and in almost 66% of cases, the students' target and fallback programs belong to the same field.[18]

3.2 Estimation strategy

Admission to the target program p for student i depends on whether the student's admission score for the program (s_{ip}) exceeds the program's cutoff score in the year t in which the student applies ($c_{t(i)p}$). The cutoff score for each program is defined as the midpoint between the admission score of the last admitted applicant and the first waitlisted applicant during the first round of admissions.

Our running variable r_{ip} measures the difference between the student's admission score for the target program and the program's cutoff score ($s_{ip} - c_{t(i)p}$). The treatment variable, $Selective_{ip}$, is equal to 1 if student i is admitted in the first round to the more selective target program, and 0 if the student is admitted instead to the less selective fallback program. It is determined as follows:

$$Selective_{ip} = \begin{cases} 1 & \text{if } r_{ip} \geq 0 \\ 0 & \text{if } r_{ip} < 0 \end{cases} \tag{1}$$

Appendix Table A.1 illustrates the variation we exploit using two examples. Student A's target program is their first choice. Their second option, which is 26 percentile points less selective, is their fallback. This student was marginally rejected from the target program (scoring 6.90 points below the cutoff) and was admitted to his fallback program. Similar to student A, student B's target program is their first choice and their fallback option is their second choice. Unlike student A, this student was admitted in the first round to the target program (with a score of 4.85 points above the cutoff), avoiding the need to fall back to the less preferred and less selective second option. Therefore, the treatment variable *Selective* is 0 for student A and 1 for student B.

[18] We classify programs into fields of study using the Cine-UNESCO 2013 classification (UNESCO Institute for Statistics, 2015), which defines 10 distinct fields. As noted by Hastings et al. (2013) and Aguirre et al. (2024), it is not uncommon for students in Chile to be at the margin of admission between programs in different fields. Similar patterns have been observed by Kirkeboen, Leuven and Mogstad (2016) in Norway.

We estimate the following equation:

$$Y_i = \beta_0 + \beta_1 Selective_{ip} + f(r_{ip}) + \varepsilon_{ip} \tag{2}$$

, where Y_i is an outcome for student i. Our main outcomes are a binary variable indicating whether the student graduated from the first university degree they enrolled in, and the time to graduation for those who completed their degree. We only consider cases where the degree was completed within nine years of taking the university admission exam, as this is the maximum time we can observe graduation outcomes for our final cohort. We also examine the likelihood of graduating from any university program, along with other outcomes, such as the likelihood of dropping out or transferring to a different program. $f(r_{ip})$ is a polynomial of the running variable, which varies at both sides of the cutoff. We use a linear polynomial and a triangular kernel, and the bias correction and inference methods proposed in Calonico, Cattaneo and Titiunik (2014) and Calonico, Cattaneo and Farrell (2020). We cluster our standard errors at the individual level, as some students have more than one observation, as explained in Section 3.1. We use a bandwidth of 25 points at each side of the cutoff, following Hastings, Neilson and Zimmerman (2013), and show that our results are robust to using alternative bandwidths.

A requirement for identification is that crossing the admission threshold generates a sizable increase in the likelihood of enrolling in the relatively more selective target program. Figure 1 shows the relationship between our running variable and enrollment in the target program. We find a large and statistically significant jump in the likelihood of enrollment at the cutoff. Specifically, being narrowly admitted to a more selective program in the first round increases the likelihood of enrolling in that program in that same year by 45 percentage points. There are several reasons for the imperfect compliance. At the left of the cutoff, 34% of students who were waitlisted in the first round are offered a spot in the target program in the second round of admissions and take it. Similarly, at the right of the cutoff, 5% of students enroll in a higher-ranked SUA program in the second round. Furthermore, some applicants who were marginally admitted to the target program in the first round end up enrolling in a program offered at an institution that does not participate in the centralized admission system (10%), or do not enroll at all and re-apply and enroll in university in the next two years (5%). As a result of this imperfect compliance, our coefficient β_1 measures the effect of being *admitted* to a more selective program relative to the next-choice option—the intent-to-treat effect. For comparison, we also report the results of estimates using admission to the target program as an instrument for enrollment in that program (i.e., a fuzzy regression discontinuity design).

3.3 Validity checks

As in any regression discontinuity design, the causal interpretation of our estimates requires that applicants just below the cutoff be comparable to those just above the cutoff in terms of baseline determinants of our outcome variables. Precise manipulation of the running variable in this context would require some students to anticipate the admission cutoffs, and then strategically submit their preferences to programs to which they would be marginally admitted. Such manipulation is highly unlikely in this context, as the cutoff for each program is determined by demand and supply after students' preferences are submitted, and varies substantially from year to year (see Appendix Figure A.2).[19] Consistently, we find that the density of our running variable is continuous at the cutoff (Panel A of Figure 2), and we fail to reject the null hypothesis of no manipulation in the Cattaneo, Jansson and Ma (2018) test (p-value=0.671).

We also examine whether the predetermined characteristics of applicants are continuous at the cutoff and report the results of these estimations in Panel B of Figure 2. Out of 21 characteristics, we find statistically significant discontinuities at the cutoff at the 10% level for only 3, which is what we would expect by chance, and these differences are small. In particular, we find that applicants at the right of the admission cutoff are 1.5 percentage points less likely to be female, are 1 percentage point more likely to come from a household where their father was the household head, and have an average math and language PSU score that is 0.9% of a standard deviation higher. Importantly, our results are robust to controlling for students' predetermined characteristics (see Section 4.2 below).

4 Results

Our main results are presented in Table 2. We find that students who were marginally admitted to a more selective program have a 2.3 percentage point lower likelihood of graduating in 9 years from the first program they enrolled in (column 1), compared to a mean of 48.3% for students marginally admitted to a less selective program (a 4.8% decrease). This jump at the cutoff is statistically significant at the 1% level, and can be clearly seen in Panel A of Figure 3. This decrease in the likelihood of graduating is mirrored by a rise in the likelihood of dropping out (column 3 of Table 2), whereas there is no effect on the likelihood of remaining enrolled in the same program after 9

[19]More than half of the oversubscribed SUA programs in our sample experienced a cutoff change of more than 10 points compared to the previous year.

years (column 2). We also find that the 2.4 percentage point increase in dropout rates is matched by an almost equivalent rise (2.1 percentage points) in the likelihood of enrolling in another university program (column 4), with a small and statistically insignificant effect (0.5 percentage points) in the likelihood of graduating from a different university program (column 5).

In Table 3, we present the results on graduation rates and time to graduation for students' initial university program (columns 1 and 3) and for any university program (columns 2 and 4). Overall, we find a 1.9 percentage point drop in the likelihood of obtaining any university degree after 9 years (column 2), a result statistically significant at the 1% level, and also seen graphically in Panel B of Figure 3. For students who do graduate, marginal admission to a more selective program delays graduation from their first program by 0.089 years (a 1.3% increase from the control mean of 6.74 years) and by 0.11 years for any program.

Using a fuzzy regression discontinuity design, we find that enrolling in the relatively more selective program reduces students' likelihood of graduating from their first program by 5.2 percentage points and decreases the likelihood of obtaining any university degree by 4.2 percentage points. These treatment-on-the-treated estimates apply to compliers—students whose first-round admission to the more selective program leads them to enroll in it.

As we explain in Section 3.1, our sample excludes applicants who did not enroll in any university degree in the three years after applying through the SUA (5.3% of those offered a spot in the first round of admissions), as most of our outcomes are only defined for enrolled students. If we instead include students who did not enroll in any university three years after first applying, we find a 1.3 percentage point decrease in the likelihood of obtaining any university degree. This decrease is statistically significant at the 10% level (p-value=0.067).[20]

We explore the timing of dropouts in Table 4. We find that students who are marginally admitted to a more selective program are more likely to drop out from the first program they enroll in after one (1.2 percentage points), two (0.9 percentage points), and three years (0.9 percentage points). These findings highlight the costs associated with admission to a more selective program, as some students spend several years paying for and working toward a degree they do not complete.

The estimations reported in column 4 of Table 2 showed that students marginally

[20]There is a small difference at the cutoff in the likelihood of enrolling in university. Students marginally admitted to a more selective program are 0.72 percentage points more likely to enroll in university in the following three years than students who were marginally denied admission (statistically significant at the 5% level).

admitted to a more selective program were 2.1 percentage points more likely to enroll in another university program after dropping out. In Table 5, we study the type of program students subsequently enroll in, after dropping out from their first degree. The majority of these marginal dropouts enroll in a program that is less selective than their target program (column 3). These students enroll in a different university (column 5) within the SUA system (column 6). Finally, marginal dropouts are more likely to enroll in a program that belongs to a different field of study than their first program (columns 8-9).

4.1 Heterogeneous effects

In this subsection, we test for heterogeneous effects by household income, student ability, and program selectivity. We measure household income using income categories reported by students in the survey they complete when they take the PSU,[21] student ability using math and language PSU scores, and program selectivity using our measure of selectivity for the target program. For each of these measures, we split the sample into two groups based on whether the student is above or below the sample median in their same cohort. We then separately estimate equation (2) for students above and below the median.

In Table 6, we present our main results by household income. As shown in column 1, both higher- and lower-income students experience a similar decline in the likelihood of graduating from their first program after being marginally admitted to a more selective degree (2.3 and 2.4 percentage points, respectively).[22] However, a significant difference emerges when considering the probability of graduating from any program (column 2). For higher-income students, the effect of marginal acceptance to a more selective program on the likelihood of obtaining any university degree is smaller (1.2 percentage points) and not statistically significant at conventional levels. In contrast, for lower-income students, the effect is as large as the decline in graduate rates for the first program. These differences arise because high-income students who fail to graduate from their first program after marginal admission to a more selective program often enroll in another program and eventually graduate (Appendix Table A.3). Conversely, lower-income students marginally admitted to a more selective program are not more likely to enroll in another program after dropping out. This is likely related to the fact that 77% of the lower-income students

[21]The income reported in this questionnaire is not used to allocate grants or scholarships, thus there is no incentive to misreport it.

[22]This does not imply that lower-income students would face the same drop in graduation rates if they enrolled in the same programs as their higher-income counterparts. Students from households below the median income have a lower math/language PSU score than those above the sample median (percentile 40 vs. 54, on average), and are thus at the margin of admission at less selective programs (percentile 60 vs. 68, on average).

are studying with government scholarships or grants, whereas only 42% of the higher-income students receive financial aid from the government.[23] Students with financial aid might have difficulty securing funding for the duration of a new program, as explained in Section 2, making them less likely to enroll elsewhere after dropping out of their initial degree.

The results when splitting our sample by student ability are similar to those obtained when splitting the sample by household income (Table 7). This is not surprising, as household income and PSU scores are highly correlated.[24] Finally, we present our results by program selectivity in Table 8. While the effects are more pronounced for above-median selectivity programs, they are evident for relatively lower selectivity programs as well. Specifically, marginal admission to a relatively more selective program reduces graduation likelihood from the first program by 2.5 percentage points for above-median selectivity programs and 2.1 points for below-median selectivity programs (column 1).

Overall, our results indicate that the negative effects of marginal admission to a relatively more selective program are disproportionately borne by lower-income students and those with lower academic ability. These students face larger declines in graduation rates and are less able to recover by graduating from alternative programs, highlighting the uneven impact of selectivity on educational outcomes.

4.2 Robustness checks

Although we use a bandwidth of 25 points around the cutoff in our estimations, our results are robust to using alternate bandwidths, as shown in Appendix Figure A.3. Our results are also unchanged if we control for baseline characteristics (Appendix Table A.6).

One should keep in mind that relatively more selective programs may differ in ways that could mechanically affect the likelihood of graduating. We examine these differences by conducting our estimations using the characteristics of the program to which the student was admitted in the first round as the dependent variable, and present the results in Appendix Tables A.7-A.8. We find that relatively more selective programs are more expensive (0.369 million Chilean pesos of 2024 per year more, or 9%), and are slightly longer (0.343 semesters more, from a mean of 9.794 semesters). Although the relatively more selective programs are more likely to be located in the province of Santiago (4.8

[23]The data on government financial aid is available from 2008 onward, and does not include the CAE, which is a government-backed loan managed directly by private banks. It does include data on financial aid such as the *Fondo Solidario de Crédito Universitario, Beca Nuevo Milenio*, and *Beca Juan Gómez Milla*, which are the most common scholarships in our sample.

[24]60% of the higher-income students in our sample are above the median in terms of math/language PSU scores, compared to only 38% of the lower-income students.

percentage points), there are no differences in the cutoff in the likelihood of being admitted to a program located in the student's province. We also find some changes at the cutoff in the program's field of study. In particular, more selective programs are more likely to belong to the health field (4.1 percentage points), and less likely to be in education (3.8 percentage points). Importantly, our estimates are robust to restricting our sample to cases in which the student's target and fallback program are similar in terms of duration, location, field of study, or major (Figure 4).[25] This shows that the decrease in graduation rates that we find is not mechanically driven by differences in the requirements, duration, or location of the program that the student was admitted to.

Finally, our results are robust to changes in the minimal selectivity difference between target and fallback programs. As shown in Figure 5, the effect on the likelihood of graduating from the initial program becomes negative, although marginally insignificant (p-value=0.104) when a minimal selectivity difference of 5 percentile points between the target and fallback programs is imposed. As expected, this effect becomes larger, though less precise, as the selectivity differences increase.

4.3 Cost-benefit exercise

In this section, we perform a basic cost-benefit exercise to assess whether students admitted to the more selective target program benefit from attending it, compared to their less selective fallback option, even when their likelihood of graduating is lower. The lower graduation rate and higher tuition of the target program may still be offset if its graduates earn substantially higher salaries in the labor market.

We calculate the expected net present value of each option at the time of enrollment, combining annual tuition payments, the probability of graduating, and the expected gross earnings associated with graduation and dropout.[26]

We assume that students enroll at age 18, and retire at age 60. For simplicity, we assume that both programs last five years, and that students who do not graduate leave their program after two years. We discount future costs and earnings at an annual rate of 3% and assume a real growth rate in gross wages of 5% per year, following (Mountjoy, 2026). We use the estimated graduation rate from students' initial program for students just to the left of the cutoff as the fallback-program graduation probability

[25] The programs in our sample are divided into 167 different majors, based on the definitions provided by the Chilean Subsecretary of Higher Education (SIES).

[26] This stylized exercise abstracts from taxes and from financial aid that may reduce or alter the timing of students' out-of-pocket tuition payments. It should therefore be interpreted as a comparison of gross earnings and listed tuition costs, rather than of students' disposable income.

and adjust this rate by our estimated 2.3 percentage point decline in degree completion to obtain the corresponding probability for target-program students. Finally, we assume that students who leave either program without graduating earn the minimum wage, whereas graduates of the fallback program earn the average gross wage observed among graduates of that program, which we obtain from *MiFuturo*.[27]

Overall, we find that, for students at the admission margin, the expected net present values of the target and fallback programs are equal when the gross wage premium associated with graduating from the target program is 2.73%.[28]

To assess whether a wage premium of this magnitude is plausible, we estimate the jump at the cutoff in the average gross wage of graduates from the program to which students were admitted to, using data from *MiFuturo*.[29] We report the results in Appendix Table A.9. Using annualized gross wages in 2024 Chilean pesos (CLP), we find that, at the cutoff, the average wage difference between target and fallback programs is 1.662 million CLP. This corresponds to a 9.7% increase relative to the 17.2 million CLP earned annually by graduates from fallback programs immediately to the left of the cutoff.

This comparison should not be interpreted as the causal wage gain that marginally admitted students would obtain by graduating from the target rather than the fallback program. The *Mi Futuro* data report average wages among graduates of each program, and these graduates may differ systematically across target and fallback programs in ways that are unrelated to the effect of attending the more selective option. Thus, the observed wage gap of 9.7% reflects both potential returns to graduating from a more selective program and differences in the characteristics of students who complete target and fallback programs.

Nevertheless, the wage premium above 2.73% required for the target program to have a larger expected net present value than the fallback program is substantially smaller than the observed 9.7% difference in earnings between average graduates of target and fallback programs near the cutoff. Therefore, under reasonable assumptions,[30] enrollment in the more selective target program remains ex ante advantageous despite its lower graduation probability.

[27] *MiFuturo* is a website that belongs to the Subsecretary of Higher Education, which reports statistics on wages and employability of graduates of different programs. We obtain data on the average salaries of graduates of different programs four years after graduation. More details available in https://www.mifuturo.cl/.

[28] For further details on this exercise, see Appendix B.

[29] We were able to match more than 85% of target programs and 78% of fallback programs in our sample.

[30] More than 72% of the observed difference in average wages between target and fallback programs would need to reflect selection or other compositional differences among their graduates for the target program to have a lower expected net present value than the fallback option.

5 Why does selectivity lead to lower degree completion?

This section examines the mechanisms underlying our findings. We first explore why students marginally admitted to more selective programs are less likely to graduate from the initial program they enroll in. We then analyze why, despite many of these marginal dropouts re-enrolling elsewhere, they are not more likely to complete a university degree overall.

There are different potential mechanisms through which admission to a more selective program may result in lower graduation rates. First, more selective programs typically have higher academic rigor, possibly leading to lower graduation rates for students at the margin who struggle to meet the program's demands.[31] This greater academic rigor may reflect a more demanding curricula, or the fact that instructors adapt their teaching and evaluations to the ability of their students, which is by definition higher in more selective programs (de Roux and Riehl, 2022).[32] Second, marginal admission to a more selective program implies having a lower rank, as compared to students marginally denied admission, and thus admitted to their fallback program. Specifically, we observe a 67 percentage point drop in ordinal rank at the cutoff (Appendix Figure A.4). There are studies showing that within the same university program, students randomly assigned to classes in which they have a lower rank have worse academic outcomes, conditional on own and average peer ability (Elsner, Isphording and Zölitz, 2021; Bertoni and Nisticò, 2023).[33] Having a lower ranking could thus decrease graduation rates due to its negative effect on students' self-concept, their perceived comparative advantage, or their expectations (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020).

As these factors all change at the cutoff, it is challenging to disentangle the individual contribution of each mechanism. Similar to Ribas, Sampaio and Trevisan (2020), we can isolate the effect of ordinal rank from academic rigor by re-estimating our model for the sample of students at the margin of admission between two programs with similar selectivity levels.[34] More specifically, we focus on cases where the difference in selectivity

[31] It is not obvious however that more selective programs are more academically rigorous. In India, for example, Sekhri (2020) finds that although students marginally admitted to elite colleges obtain higher salaries, they do not obtain higher scores in their university exit exam.

[32] Attending a program with better peers could also result in worse outcome if teachers grade on a curve. However, informal consultation with professors from different departments at 15 universities reveals that grading on a curve is highly uncommon in Chilean universities.

[33] Several studies also find that students with a lower rank in K-12 education tend to achieve worse educational outcomes. See Delaney and Devereux (2022) for a comprehensive literature review on rank effects.

[34] Ribas et al. (2020) use a RD design to examine the effect of being placed in the high vs. low track in a flagship university in Brazil. They find that students marginally assigned to the higher class have worse academic outcomes, and show that these results are explained by differences in rank, rather than peer

between the target and fallback programs is smaller than or equal to 5 percentile points. In this sample, students marginally admitted to the target program have an average ordinal rank that is 43 percentile points lower than those marginally denied admission (and admitted to the fallback program), with minimal differences in selectivity. While the jump in rank at the cutoff is smaller than in our main sample (43 vs. 67 percentile points), it is sizable in comparison to other studies finding negative rank effects (e.g., Elsner and Isphording, 2017). We find that students marginally admitted to the target program are 4.2 percentage points *more* likely to graduate from their initial program compared to those who are marginally rejected from their target program (column 1, Appendix Table A.10). These results show that the negative effects of selectivity we observe are not driven by ordinal rank, and suggests that they are instead driven by higher academic rigor.

While the previously explored mechanisms explain why students marginally admitted to more selective programs are less likely to graduate from their initial program, it is also important to understand why, even though many of these marginal dropouts later enroll in another program, they are not more likely to complete a university degree. One potential explanation is that institutional barriers make transferring and graduating elsewhere cumbersome. Programs in Chile's centralized system have relatively fixed curricula, with few electives and limited cross-department credit recognition. Students who wish to change their major, even within the same university, must apply again through the centralized system, and request credit transfers. The transfer behavior we observe from students in this context is likely to make these frictions even more consequential. As shown in Table 5, students marginally admitted to a more selective program who drop out are more likely to re-enroll in a different university and in a different field of study, where their previously completed coursework is less likely to count toward the new degree. This helps explain why re-enrollment does not offset the initial decline in program completion.

Another possible explanation is that financial constraints may limit students' ability to obtain a degree from another program. As discussed in Section 2, roughly two-thirds of university students in Chile rely on government-backed loans or scholarships that can only be used for a limited number of years and must be formally transferred when changing programs. Students who rely on financial aid for their education may struggle to secure enough funding to finance a degree in a new program. We assess whether this mechanism helps explain our results by examining heterogeneity in the effects by students' reliance on financial aid.

As shown in Table 9, our results are driven by students who have financial aid. We consider the scholarships *Beca Vocación de Profesor*, *Beca Juan Gómez Milla*, *Beca Bicentenario*,

quality.

Beca Nuevo Milenio, and the loan *Fondo Solidario de Crédito Universitario* as these schemes provide a substantial amount toward the fees, ranging from 600,000 CLP (*Beca Nuevo Milenio*) to a full waiver (*Beca Vocacion de Profesor*). Financial aid information is only available since 2008 and it does not include one of the main loan schemes, the *Crédito con Aval del Estado*, as this one is contracted directly with a bank and through a government agency. Financial aid partly explains why we find that higher-income students marginally admitted to a more selective program often re-enroll and eventually graduate elsewhere, whereas lower-income students who are more likely to receive financial aid do not, as shown in Section 4.1.

Taken together, the evidence in this section suggests that the decline in degree completion is driven by two related margins. Marginal admission to a more selective program appears to reduce completion in the initial program through greater academic demands, rather than through students' lower ordinal rank. At the same time, institutional and financial frictions limit students' ability to recover from this initial setback by completing a degree elsewhere, particularly among students who rely on financial aid.

6 Conclusions

This paper provides new evidence on the effects of selectivity on university degree completion, using a regression discontinuity design within Chile's centralized university admission system. Our results question the prevailing view in the literature by showing that marginal admission to a more selective program reduces the likelihood of graduation, both from the initial program and any university program. Specifically, students admitted to a more selective program are 2.3 percentage points less likely to graduate from their first program and 1.9 percentage points less likely to complete any university degree. These effects are particularly pronounced for lower-income students, who face greater barriers to transferring and completing a degree elsewhere after dropping out.

We find suggestive evidence that the negative effects of selectivity are due to the higher academic rigors, rather than rank. It is important to note that our findings apply specifically to students near the admission margin of more selective programs and may not generalize to all students in these programs.

Our findings underscore the importance of informing applicants of the trade-offs associated with program selectivity (Arcidiacono et al., 2025), particularly in the case of disadvantaged students who face greater difficulties in completing a degree after dropping out of their initial program. At the same time, our cost-benefit analysis indicates that under reasonable assumptions, it is ex ante advantageous for marginal students to enroll in more selective programs, given the substantial wage gains they can expect upon graduation. To fully realize these benefits, universities should enhance their support structures, thus helping students navigate and succeed in these settings (Aucejo et al., 2025).

References

Aguirre, Josefa, Juan Matta, and Ana María Montoya (2024) "Joining the Old Boys' Club: Women's Returns to Majoring in Technology and Engineering," Working Paper.

Anelli, Massimo (2020) "The Returns to Elite University Education: A Quasi-Experimental Analysis," *Journal of the European Economic Association*, 18 (6), 2824–2868.

Arcidiacono, Peter, Esteban M. Aucejo, Arnaud Maurel, and Tyler Ransom (2025) "College Attrition and the Dynamics of Information Revelation," *Journal of Political Economy*, 133 (1), 53–110.

Arcidiacono, Peter, Esteban M. Aucejo, and Ken Spenner (2012) "What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice," *IZA Journal of Labor Economics*, 1 (1), 5.

Arcidiacono, Peter and Michael Lovenheim (2016) "Affirmative Action and the Quality–Fit Trade-Off," *Journal of Economic Literature*, 54 (1), 3–51.

Aucejo, Esteban M., Jacob French, Paola Ugalde Araya, and Basit Zafar (2025) "Understanding Gaps in College Outcomes by First-Generation Status," Working Paper 34129, National Bureau of Economic Research.

Barahona, Nano, Cauê Dobbin, and Sebastián Otero (2023) "Affirmative Action in Centralized College Admissions Systems," Working Paper.

Barrios-Fernández, Andrés (2022) "Neighbors' Effects on University Enrollment," *American Economic Journal: Applied Economics*, 14 (3), 30–60.

Bertoni, Marco and Roberto Nisticò (2023) "Ordinal Rank and the Structure of Ability Peer Effects," *Journal of Public Economics*, 217, 104797.

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.

Bleemer, Zachary (2022) "Affirmative Action, Mismatch, and Economic Mobility After California's Proposition 209*," *Quarterly Journal of Economics*, 137 (1), 115–160.

Bordon, Paola and Chao Fu (2015) "College-major Choice to College-Then-Major Choice," *Review of Economic Studies*, 82 (4), 1247–1288.

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.

Calonico, Sebastian, Matias D Cattaneo, and Max H Farrell (2020) "Optimal Bandwidth Choice for Robust Bias-Corrected Inference in Regression Discontinuity Designs," *The Econometrics Journal*, 23 (2), 192–210.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik (2014) "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 82 (6), 2295–2326.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma (2018) "Manipulation Testing Based on Density Discontinuity," *The Stata Journal*, 18 (1), 234–261, Publisher: SAGE Publications.

Cohodes, Sarah R. and Joshua S. Goodman (2014) "Merit Aid, College Quality, and College Completion: Massachusetts' Adams Scholarship as an In-Kind Subsidy," *American Economic Journal: Applied Economics*, 6 (4), 251–285.

Delaney, Judith M and Paul J Devereux (2022) "Rank Effects in Education: What Do We Know So Far?" *Handbook of Labor, Human Resources and Population Economics*, 1–24.

Dillon, Eleanor Wiske and Jeffrey Andrew Smith (2020) "The Consequences of Academic Match Between Students and Colleges," *Journal of Human Resources*, 55 (3), 767–808.

Elsner, Benjamin and Ingo E Isphording (2017) "A Big Fish in a Small Pond: Ability Rank and Human Capital Investment," *Journal of Labor Economics*, 35 (3), 787–828.

Elsner, Benjamin, Ingo E Isphording, and Ulf Zölitz (2021) "Achievement Rank Affects Performance and Major Choices in College," *Economic Journal*, 131 (640), 3182–3206.

Goodman, Joshua, Michael Hurwitz, and Jonathan Smith (2017) "Access to 4-Year Public Colleges and Degree Completion," *Journal of Labor Economics*, 35 (3), 829–867.

Hastings, Justine S, Christopher A Neilson, and Seth D Zimmerman (2013) "Are Some Degrees Worth More Than Others? Evidence from College Admission Cutoffs in Chile," Working Paper 19241, National Bureau of Economic Research.

Hoekstra, Mark (2009) "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach," *Review of Economics and Statistics*, 91 (4), 717–724.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad (2016) "Field of Study, Earnings, and Self-Selection*," *Quarterly Journal of Economics*, 131 (3), 1057–1111.

Light, Audrey and Wayne Strayer (2000) "Determinants of College Completion: School Quality or Student Ability?" *Journal of Human Resources*, 299–332.

Loury, Linda Datcher and David Garman (1995) "College Selectivity and Earnings," *Journal of Labor Economics*, 13 (2), 289–308.

Lovenheim, Michael and Jonathan Smith (2023) "Returns to Different Postsecondary Investments: Institution Type, Academic Programs, and Credentials," in *Handbook of the Economics of Education*, 6, 187–318: Elsevier.

Mountjoy, Jack (2026) "Marginal Returns to Public Universities," *Quarterly Journal of Economics*, 141 (1), 429–497.

Murphy, Richard and Felix Weinhardt (2020) "Top of the Class: The Importance of Ordinal Rank," *Review of Economic Studies*, 87 (6), 2777–2826.

OECD (2014) *Education at a Glance 2014: OECD Indicators*, Education at a Glance: OECD, 10.1787/eag-2014-en.

——— (2022) *Education at a Glance 2022: OECD Indicators*, Education at a Glance: OECD, 10.1787/3197152b-en.

Ribas, Rafael P, Breno Sampaio, and Giuseppe Trevisan (2020) "Short-and Long-Term Effects of Class Assignment: Evidence from a Flagship University in Brazil," *Labour Economics*, 64, 101835.

de Roux, Nicolás and Evan Riehl (2022) "Do College Students Benefit from Placement into Higher-Achieving Classes?" *Journal of Public Economics*, 210, 104669.

Sekhri, Sheetal (2020) "Prestige Matters: Wage Premium and Value Addition in Elite Colleges," *American Economic Journal: Applied Economics*, 12 (3), 207–225.

Tincani, Michela M, Fabian Kosse, and Enrico Miglino (2023) "College Access When Preparedness Matters: New Evidence from Large Advantages in College Admissions," Working Paper.

UNESCO Institute for Statistics (2015) "International Standard Classification of Education: Fields of Education and Training 2013 (ISCED-F 2013) Detailed Field Descriptions.."

Zafar, Basit (2011) "How Do College Students Form Expectations?" *Journal of Labor Economics*, 29 (2), 301–348.

Zimmerman, Seth D (2014) "The Returns to College Admission for Academically Marginal Students," *Journal of Labor Economics*, 32 (4), 711–754.

——— (2019) "Elite Colleges and Upward Mobility to Top Jobs and Top Incomes," *American Economic Review*, 109 (1), 1–47.

Tables and Figures

Table 1: Descriptive statistics

	Selectivity diff ≥ 10 pp	All students
Sociodemographic characteristics		
Female	0.527	0.514
Lives in Metropolitan region	0.304	0.351
Public high school	0.302	0.287
Private subsidized high school	0.539	0.506
Private high school	0.159	0.207
Father is HH head	0.599	0.611
Mother is HH head	0.325	0.317
Mother works full-time	0.409	0.421
Father works full-time	0.593	0.603
Mother has primary education or less	0.103	0.095
Mother has comp/uncomp. secondary education	0.453	0.425
Mother has comp/uncomp. university education	0.369	0.399
Mother has unknown education	0.074	0.081
Father has primary education or less	0.105	0.097
Father has comp/uncomp. secondary education	0.379	0.354
Father has comp/uncomp. university education	0.365	0.396
Father has unknown education	0.151	0.153
PSU scores and GPA		
Average math and language PSU percentile	47.858	52.698
Average math and language PSU score	586.511	600.195
GPA	607.599	619.068
Within-school GPA rank (for 2013-2017)	630.848	645.261
Number of students	241,488	333,833

Notes: This table presents descriptive statistics of the students in our sample (column 1), and the sample without restricting the selectivity differences between target and fallback (in column 2).

Table 2: Effect on university degree completion

	First program enrolled			Another program	
	Graduated (in ≤ 9 yrs.)	Still enrolled (after 9 yrs.)	Dropped out	Enrolled in another program	Graduated in ≤ 9 yrs. (another program)
RD Estimate	-0.023***	-0.001	0.024***	0.021***	0.005
	(0.007)	(0.003)	(0.007)	(0.007)	(0.005)
Dep. variable mean	0.483	0.044	0.474	0.314	0.137
Observations	271,883	271,883	271,883	271,883	271,883
Obs. within bandwidth	148904	148904	148904	148904	148904

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in column 1 is a dummy for whether the student obtained a university degree from the first program they enrolled in for the nine-year period after taking the PSU. The dependent variable in column 2 is a dummy for whether the student is still enrolled in that program after nine years, and the dependent variable in column 3 is a dummy for whether the student dropped out of that program. The dependent variable in column 4 is a dummy for whether the student enrolled in another university program, and the dependent variable in column 5 is a dummy for whether the student obtained a university degree from any program in the 9 years after taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Effect on university degree completion and time to graduation

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
RD Estimate	-0.023***	-0.019***	0.089***	0.112***
	(0.007)	(0.007)	(0.026)	(0.024)
Dep. variable mean	0.483	0.619	6.740	6.940
Observations	271,883	271,883	130,046	166,981
Obs. within bandwidth	148904	148904	70867	91504

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in columns 1 and 2 are dummies for whether, in the nine year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Effect on likelihood and timing of dropout

	Dropped out from first program enrolled			
	After 1 year	After 2 years	After 3 years	After 4+ years
RD Estimate	0.012**	0.009**	0.009**	-0.006
	(0.006)	(0.005)	(0.004)	(0.005)
Dep. variable mean	0.191	0.103	0.061	0.118
Observations	271,883	271,883	271,883	271,883
Obs. within bandwidth	148904	148904	148904	148904

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable is a dummy for whether the students dropped out from the first program they enrolled in at the time detailed in the column header. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Effect on likelihood of enrolling elsewhere by type of program

	Selectivity (vs. target)			University (vs. first)		Type of university		Field of study (vs. first)	
	Higher	Similar	Lower	Same	Different	SUA	Non-SUA	Same	Different
RD Estimate	0.005**	-0.003	0.022***	-0.001	0.023***	0.021***	0.000	0.008	0.015***
	(0.002)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)
Dep. variable mean	0.022	0.122	0.156	0.113	0.201	0.240	0.073	0.154	0.158
Observations	266,743	266,743	266,743	271,883	271,883	271,883	271,883	271,452	271,452
Obs. within bandwidth	146203	146203	146203	148904	148904	148904	148904	148658	148658

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable is a dummy for whether the student subsequently enrolled in another program with the characteristics detailed in the column header. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Effect on university degree completion and time to graduation – heterogeneous effects by household income

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
Panel A: Above median income				
RD Estimate	-0.023**	-0.012	0.083**	0.113***
	(0.010)	(0.010)	(0.035)	(0.031)
Dep. variable mean	0.479	0.630	6.790	6.999
Observations	153,968	153,968	74,305	97,305
Obs. within bandwidth	84335	84335	40215	53200
Panel B: Below median income				
RD Estimate	-0.024**	-0.029***	0.095**	0.106***
	(0.011)	(0.011)	(0.040)	(0.037)
Dep. variable mean	0.487	0.606	6.677	6.862
Observations	117,915	117,915	55,741	69,676
Obs. within bandwidth	64569	64569	30652	38304

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students who are below (above) the sample median in their cohort in terms of household income at the time of taking the PSU. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variables in columns 1 and 2 are dummies for whether, in the nine-year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Effect on university degree completion and time to graduation – heterogeneous effects by student ability

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
Panel A: Above median ability				
RD Estimate	-0.019*	-0.010	0.121***	0.137***
	(0.010)	(0.010)	(0.035)	(0.032)
Dep. variable mean	0.502	0.643	6.828	7.022
Observations	137,615	137,615	70,541	90,061
Obs. within bandwidth	75571	75571	37753	48825
Panel B: Below median ability				
RD Estimate	-0.027**	-0.028***	0.052	0.082**
	(0.011)	(0.010)	(0.039)	(0.036)
Dep. variable mean	0.463	0.594	6.643	6.850
Observations	134,268	134,268	59,505	76,920
Obs. within bandwidth	73333	73333	33114	42679

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students who are below (above) the sample median in their cohort in terms of average math and language PSU scores. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variables in columns 1 and 2 are dummies for whether, in the nine-year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at, or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Effect on university degree completion and time to graduation – heterogeneous effects by program selectivity

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
Panel A: Above median selectivity				
RD Estimate	-0.025**	-0.017	0.097***	0.119***
	(0.011)	(0.010)	(0.035)	(0.032)
Dep. variable mean	0.512	0.658	6.840	7.028
Observations	136,434	136,434	69,279	89,182
Obs. within bandwidth	73644	73644	37454	48568
Panel B: Below median selectivity				
RD Estimate	-0.021**	-0.020*	0.086**	0.107***
	(0.010)	(0.010)	(0.039)	(0.036)
Dep. variable mean	0.455	0.582	6.630	6.843
Observations	135,449	135,449	60,767	77,799
Obs. within bandwidth	75260	75260	33413	42936

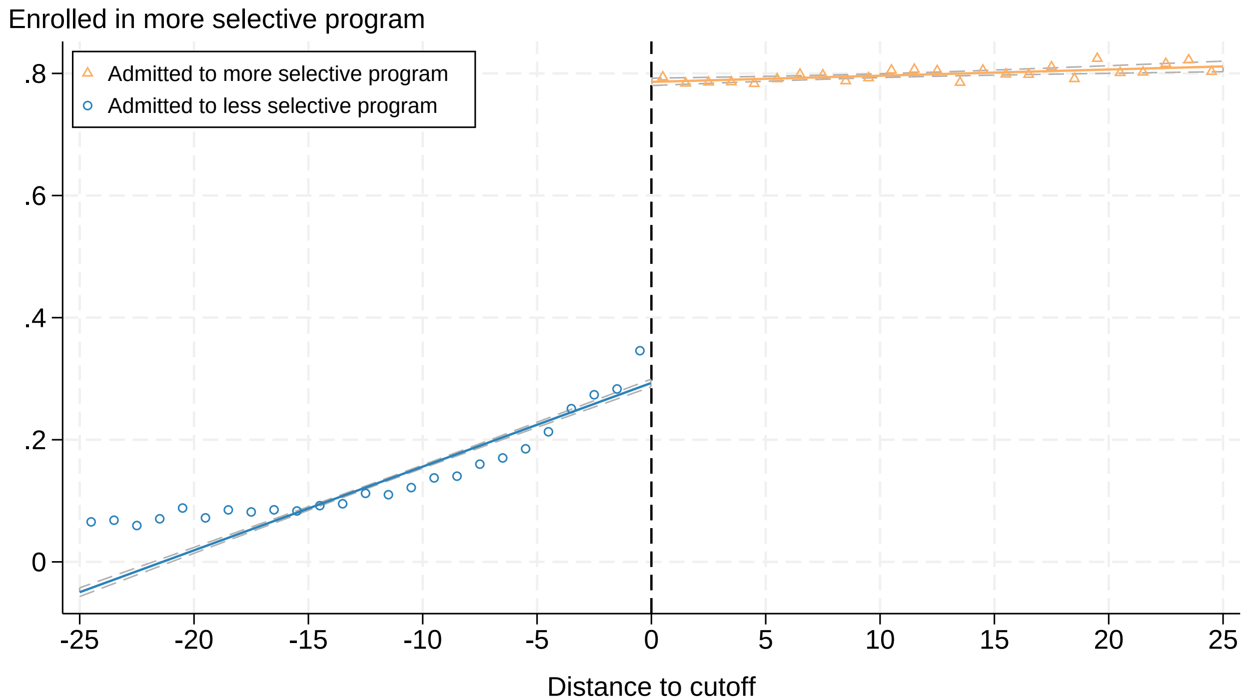
Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students whose target program is above (below) the sample median in terms of our measure of selectivity. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in columns 1 and 2 are dummies for whether, in the nine year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Effect on university degree completion and time to graduation – heterogeneous effects by financial aid

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
Panel A: Has financial aid				
RD Estimate	-0.029***	-0.027***	0.112***	0.134***
	(0.010)	(0.010)	(0.036)	(0.034)
Dep. variable mean	0.486	0.613	6.667	6.873
Observations	134,164	134,164	64,322	81,399
Obs. within bandwidth	74701	74701	35499	45233
Panel B: Does not have financial aid				
RD Estimate	-0.019	-0.007	0.077*	0.090**
	(0.012)	(0.012)	(0.043)	(0.038)
Dep. variable mean	0.482	0.629	6.816	7.009
Observations	111,495	111,495	53,779	69,956
Obs. within bandwidth	58812	58812	28324	37110

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students who have (do not have) financial aid in the following categories: BNM, BJGM, BBIC, BPV or FSCU. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variables in columns 1 and 2 are dummies for whether, in the nine-year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

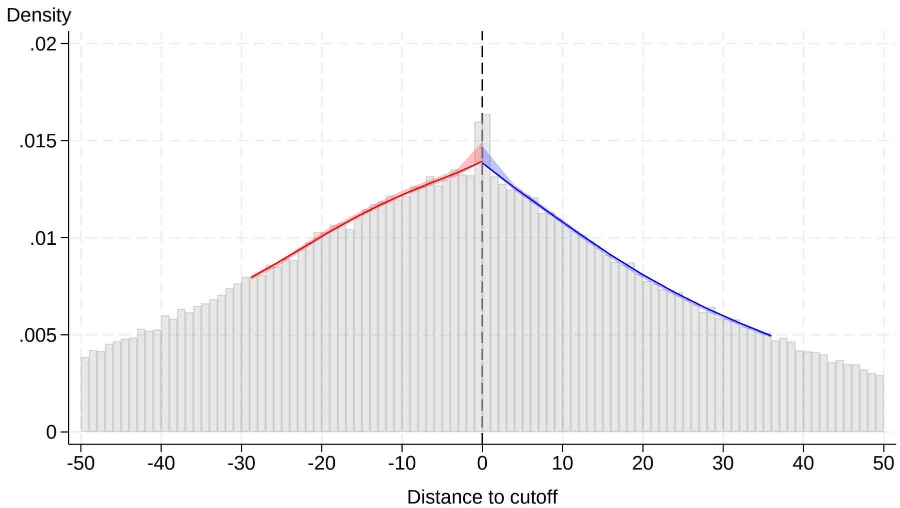
Figure 1: Effect on likelihood of enrolling in the more selective program



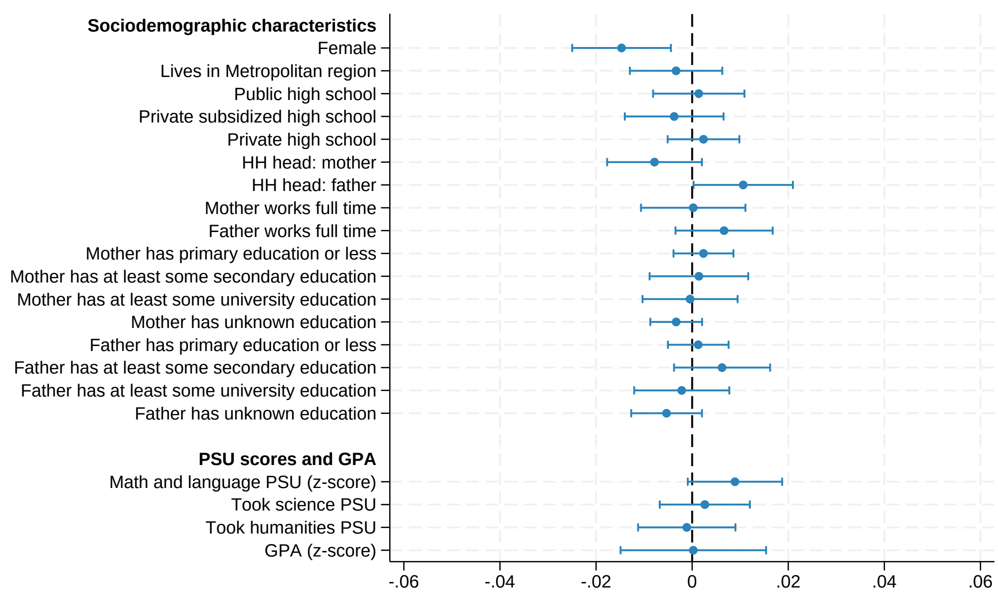
Notes: This figure plots the relationship between the likelihood of enrolling in the relatively more selective target program and the distance to the admission score cutoff of this program. The outcome variable is a dummy variable taking the value of 1 if the student enrolled in this program during the same admission cycle. Dots represent the average outcome variable in equally spaced bins. The solid lines depict a linear fit for regressions conducted on a 25-point bandwidth at each side of the cutoff using a triangular kernel; the dashed lines depict their 95% confidence intervals, with standard errors clustered at the student level.

Figure 2: Validity checks

(a) Density of the running variable



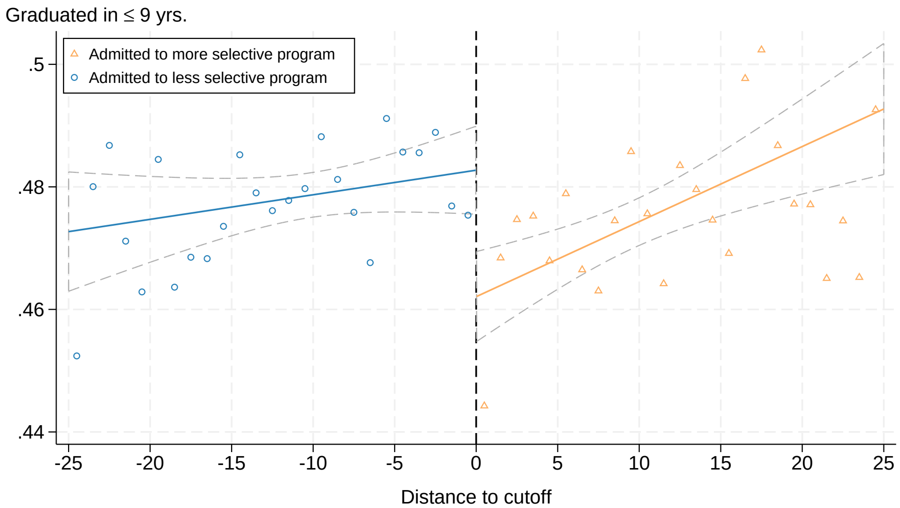
(b) Covariate balance at the cutoff



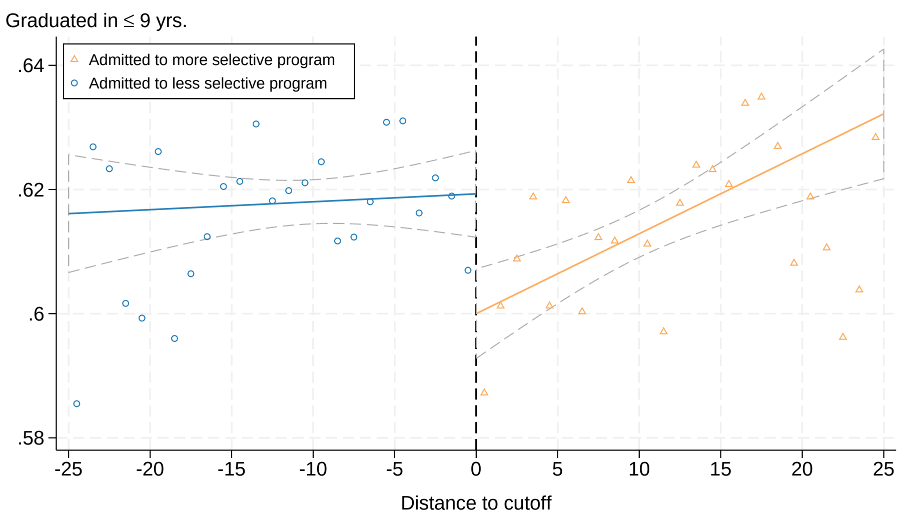
Notes: The figure in Panel B plots the density of the running variable. The figure in Panel B plots the coefficients and 95% confidence intervals of an estimation of equation (2) with the predetermined characteristics specified in the row headers as the dependent variable. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff, and we cluster the standard errors at the student level.

Figure 3: Effect on university degree completion

(a) First program enrolled

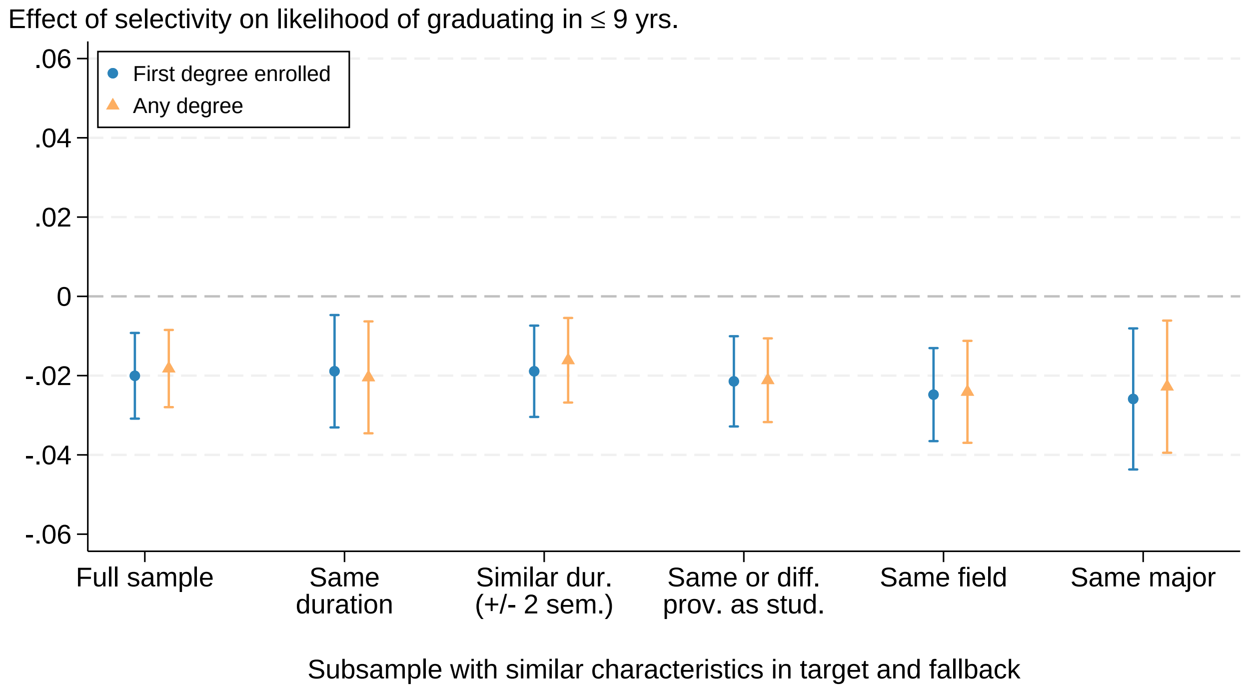


(b) Any program



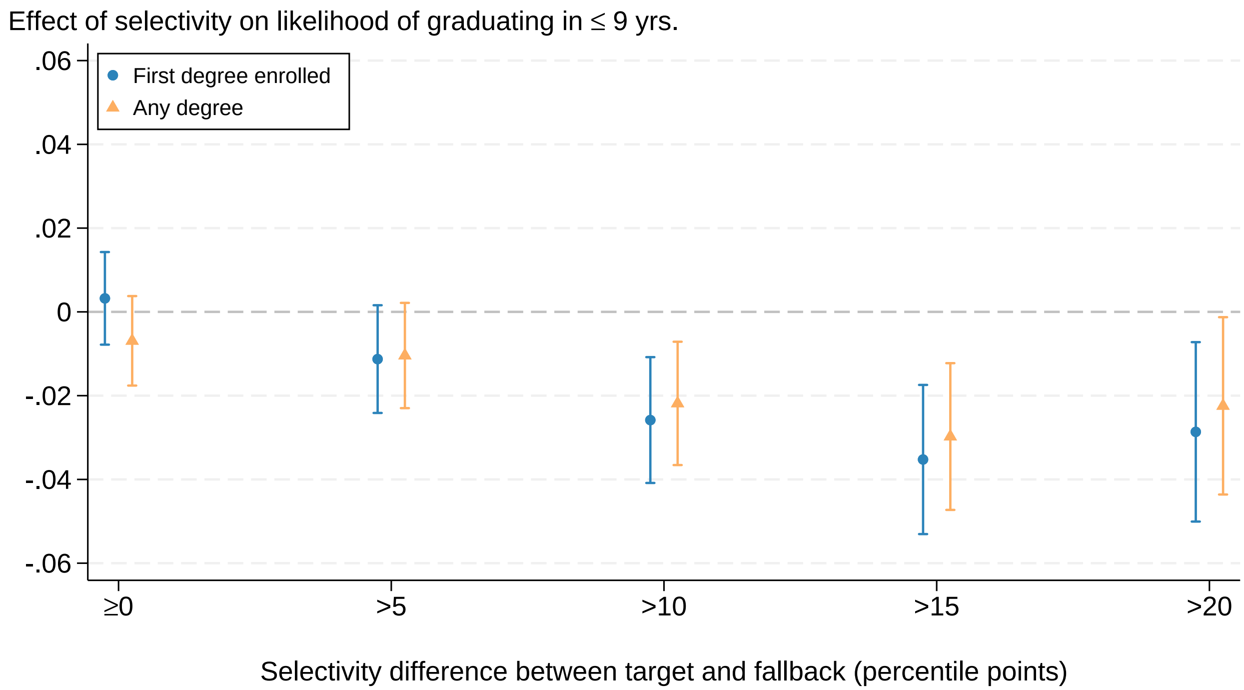
Notes: These figures plot the relationship between the likelihood of graduating and the distance to the admission score cutoff for the target program. The outcome variables in Panel A and B are dummies for whether, in the nine year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. Dots represent the average outcome variable in equally spaced bins. The solid lines depict a linear fit for regressions conducted on a 25-point bandwidth at each side of the cutoff using a triangular kernel; the dashed lines depict their 95% confidence intervals, with standard errors clustered at the student level.

Figure 4: Effect on university degree completion – robustness to sample restrictions



Notes: This figure presents the coefficient and 95% confidence interval of our RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program for different subsamples. *Same duration* is the sample in which the target and fallback program have the same duration, and *similar duration* is the subsample in which the difference in duration is two semesters or less. *Same or different province as student* is the subsample in which both the target and fallback program are located in the student's province, or both are located in a different province. *Same field* is the subsample in which the target and fallback programs belong to the same field of study, and *same major* is the subsample in which the two programs have the same major. The circular and triangular markers plot the coefficients for estimations where the dependent variables are dummies for whether, in the nine-year period after applying to university, the student obtained a university degree from the first program they enrolled in or any university program, respectively. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, restricting our sample to the subgroup of students specified on the x-axis. We cluster the standard errors at the student level.

Figure 5: Effect on university degree completion – robustness to changes in minimum selectivity difference



Notes: This figure presents the coefficient and 95% confidence interval of our RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program restricting our sample to different minimum selectivity differences between the target and fallback programs. The circular and triangular markers plot the coefficients for estimations where the dependent variables are dummies for whether, in the nine year period after applying to university, the student obtained a university degree from the first program they enrolled in or any university program, respectively. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, restricting the selectivity difference between target and fallback programs as specified in the x-axis. We cluster the standard errors at the student level.

Online Appendix for: "The pitfalls of higher selectivity: Evidence on university degree completion"

A Appendix Tables and Figures

Table A.1: Example – Applications, selectivity differences, and admission outcomes

Student	Preference order	Degree	University	Program selectivity (percentile)	Distance to program cutoff	Admission status
A	1	Construction engineering	Universidad de la Frontera	55	-6.90	Waitlisted
A	2	Construction engineering	Universidad Austral	29	31.93	Admitted in 1st round
B	1	Law	Universidad Católica del Norte	68	4.85	Admitted in 1st round
B	2	Law	Universidad de Antofagasta	32	56.30	-

Table A.2: Descriptive statistics – Target and fallback programs

	Selectivity diff $\geq$ 10 pp	All students
Target program characteristics		
Program selectivity (percentile)	64.296	66.217
Preference order	1.734	1.752
In student's province	0.534	0.552
Located in Santiago (province)	0.337	0.404
Tuition in MM CLP of 2024	4.517	4.727
Duration (semesters)	10.226	10.318
Same field as fallback	0.655	0.655
Same major as fallback	0.365	0.353
Business or law	0.169	0.169
Agriculture or veterinary	0.029	0.026
Arts or humanities	0.039	0.037
Social sciences or journalism	0.082	0.074
Natural science or math	0.048	0.046
Education	0.098	0.094
Engineering	0.245	0.256
Health	0.243	0.253
Services	0.009	0.010
Information and communication technology	0.038	0.036
Fallback program characteristics		
Program selectivity (percentile)	39.321	48.222
Preference order	3.282	3.284
In student's province	0.533	0.546
Located in Santiago (province)	0.283	0.359
Tuition in MM CLP of 2024	4.103	4.376
Duration (semesters)	9.827	9.944
Business or law	0.157	0.157
Agriculture or veterinary	0.040	0.035
Arts or humanities	0.039	0.041
Social sciences or journalism	0.073	0.071
Natural science or math	0.060	0.066
Education	0.138	0.123
Engineering	0.249	0.255
Health	0.178	0.193
Services	0.021	0.018
Information and communication technology	0.044	0.041
Observations	271,883	413,555

Notes: This table presents descriptive statistics for the target and fallback programs in our sample (column 1), and the sample without restricting the selectivity differences between target and fallback (in column 2).

Table A.3: Effect on university degree completion – heterogeneous effects by household income

	First program enrolled			Another program	
	Graduated (in ≤ 9 yrs.)	Still enrolled (after 9 yrs.)	Dropped out	Enrolled in another program	Graduated in ≤ 9 yrs. (another program)
Panel A: Above median income					
RD Estimate	-0.023**	-0.005	0.028***	0.029***	0.011
	(0.010)	(0.004)	(0.010)	(0.009)	(0.007)
Dep. variable mean	0.479	0.046	0.475	0.333	0.150
Observations	153,968	153,968	153,968	153,968	153,968
Obs. within bandwidth	84335	84335	84335	84335	84335
Panel B: Below median income					
RD Estimate	-0.024**	0.005	0.020*	0.010	-0.005
	(0.011)	(0.005)	(0.011)	(0.010)	(0.007)
Dep. variable mean	0.487	0.041	0.472	0.289	0.119
Observations	117,915	117,915	117,915	117,915	117,915
Obs. within bandwidth	64569	64569	64569	64569	64569

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students who are below (above) the sample median in their cohort in terms of household income at the time of taking the PSU. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in column 1 is a dummy for whether the student obtained a university degree from the first program they enrolled in, for the nine-year period after applying to university. The dependent variable in column 2 is a dummy for whether the student is still enrolled in that program after nine years, and the dependent variable in column 3 is a dummy for whether the student dropped out of that program. The dependent variable in column 4 is a dummy for whether the student enrolled in another university program, and the dependent variable in column 5 is a dummy for whether the student obtained a university degree from any program in the 9 year period after taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.4: Effect on university degree completion – heterogeneous effects by student ability

	First program enrolled			Another program	
	Graduated (in ≤ 9 yrs.)	Still enrolled (after 9 yrs.)	Dropped out	Enrolled in another program	Graduated in ≤ 9 yrs. (another program)
Panel A: Above median ability					
RD Estimate	-0.019*	-0.004	0.024**	0.028***	0.010
	(0.010)	(0.005)	(0.010)	(0.010)	(0.007)
Dep. variable mean	0.502	0.048	0.450	0.325	0.142
Observations	137,615	137,615	137,615	137,615	137,615
Obs. within bandwidth	75571	75571	75571	75571	75571
Panel B: Below median ability					
RD Estimate	-0.027**	0.003	0.024**	0.014	-0.001
	(0.011)	(0.004)	(0.011)	(0.010)	(0.007)
Dep. variable mean	0.463	0.040	0.498	0.301	0.131
Observations	134,268	134,268	134,268	134,268	134,268
Obs. within bandwidth	73333	73333	73333	73333	73333

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students who are below (above) the sample median in their cohort in terms of average math and language PSU scores. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in column 1 is a dummy for whether the student obtained a university degree from the first program they enrolled in, for the nine-year period after applying to university. The dependent variable in column 2 is a dummy for whether the student is still enrolled in that program after nine years, and the dependent variable in column 3 is a dummy for whether the student dropped out of that program. The dependent variable in column 4 is a dummy for whether the student enrolled in another university program, and the dependent variable in column 5 is a dummy for whether the student obtained a university degree from any program in the 9 year period after taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.5: Effect on university degree completion – heterogeneous effects by program selectivity

	First program enrolled			Another program	
	Graduated (in ≤ 9 yrs.)	Still enrolled (after 9 yrs.)	Dropped out	Enrolled in another program	Graduated in ≤ 9 yrs. (another program)
Panel A: Above median selectivity					
RD Estimate	-0.025**	-0.006	0.031***	0.030***	0.008
	(0.011)	(0.005)	(0.011)	(0.010)	(0.008)
Dep. variable mean	0.512	0.048	0.441	0.325	0.146
Observations	136,434	136,434	136,434	136,434	136,434
Obs. within bandwidth	73644	73644	73644	73644	73644
Panel B: Below median selectivity					
RD Estimate	-0.021**	0.004	0.017	0.014	0.001
	(0.010)	(0.004)	(0.010)	(0.010)	(0.007)
Dep. variable mean	0.455	0.040	0.505	0.303	0.127
Observations	135,449	135,449	135,449	135,449	135,449
Obs. within bandwidth	75260	75260	75260	75260	75260

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students whose target program is above (below) the sample median in terms of our measure of selectivity. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in column 1 is a dummy for whether the student obtained a university degree from the first program they enrolled in, for the nine-year period after applying to university. The dependent variable in column 2 is a dummy for whether the student is still enrolled in that program after nine years, and the dependent variable in column 3 is a dummy for whether the student dropped out of that program. The dependent variable in column 4 is a dummy for whether the student enrolled in another university program, and the dependent variable in column 5 is a dummy for whether the student obtained a university degree from any program in the 9 year period after taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.6: Effect on university degree completion and time to graduation – robustness to controlling for baseline characteristics

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
RD Estimate	-0.022***	-0.018**	0.090***	0.110***
	(0.007)	(0.007)	(0.026)	(0.024)
Observations	257,419	257,419	123,346	158,051
Obs. within bandwidth	141027	141027	67309	86674

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variables in columns 1 and 2 are dummies for whether, in the nine-year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. All regressions control for the baseline characteristics from Panel B of Appendix Figure 2, as well as cohort fixed effects. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.7: Effect on characteristics of the program the student was admitted to in the first round

	Tuition (in MM CLP of 2024)	Duration (semesters)	In Santiago	In student's province
RD Estimate	0.369***	0.343***	0.048***	-0.006
	(0.019)	(0.020)	(0.007)	(0.007)
Dep. variable mean	4.036	9.794	0.309	0.531
Observations	243,196	269,067	271,883	270,512
Obs. within bandwidth	133064	147370	148904	148175

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program on the characteristics of the program the student was admitted to. The dependent variable in the first column is the program's yearly tuition, measured in millions of Chilean pesos of 2024. The dependent variable in column 2 measures the duration of the program's coursework, in semesters. The dependent variables in columns 3 and 4 are dummy variables for whether the program is located in the province of Santiago, and in the student's province, respectively. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.8: Effect on the field of study of the program the student was admitted to in the first round

	Field of study									
	Business or law	Agriculture or veterinary	Arts or humanities	Soc. science or journalism	Nat. science or math	Education	Engineering	Health	Services	Inf. and communic. technology
RD Estimate	-0.001	-0.001	0.007**	0.008**	-0.004	-0.038***	0.005	0.041***	-0.014***	-0.005
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.006)	(0.006)	(0.002)	(0.003)
Dep. variable mean	0.160	0.036	0.040	0.069	0.050	0.149	0.254	0.178	0.023	0.042
Observations	270,754	270,754	270,754	270,754	270,754	270,754	270,754	270,754	270,754	270,754
Obs. within bandwidth	148243	148243	148243	148243	148243	148243	148243	148243	148243	148243

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program on the field of study of the program the student was admitted to. The dependent variable is a dummy variable for whether the program belongs to the field of study specified in the column header. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.9: Effect on average wages of graduates of the program the student was admitted to in the first round

	Wages (in MM CLP)
RD Estimate	1.662***
	(0.090)
Dep. variable mean	17.219
Observations	204,548
Obs. within bandwidth	113661

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program on the average wages four years after graduation of graduates from the program the student was admitted to, using data from MiFuturo. The dependent is the annualized gross wages in millions of Chilean Pesos. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.10: Effect on university degree completion and time to graduation – sample with minimum differences in selectivity between target and fallback

	Graduated in 9 years		Yrs. until completion	
	First program	Any program	First program	Any program
RD Estimate	0.042***	0.002	-0.018	-0.064**
	(0.011)	(0.010)	(0.035)	(0.031)
Dep. variable mean	0.519	0.683	6.996	7.168
Observations	83,707	83,707	45,418	57,581
Obs. within bandwidth	58732	58732	31551	40308

Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more preferred program. We limit the sample to observations for which the target and fallback program have a difference in selectivity smaller than 5 percentile points. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in columns 1 and 2 are dummies for whether, in the nine year period after applying to university, the student obtained a university degree from the first program they enrolled in and any university program, respectively. In columns 3 and 4, the sample is restricted to students who graduated from the first program they enrolled at or any university program, respectively. The dependent variable in columns 3 and 4 is the number of years until graduation from the first university program they enrolled in or any university program since taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

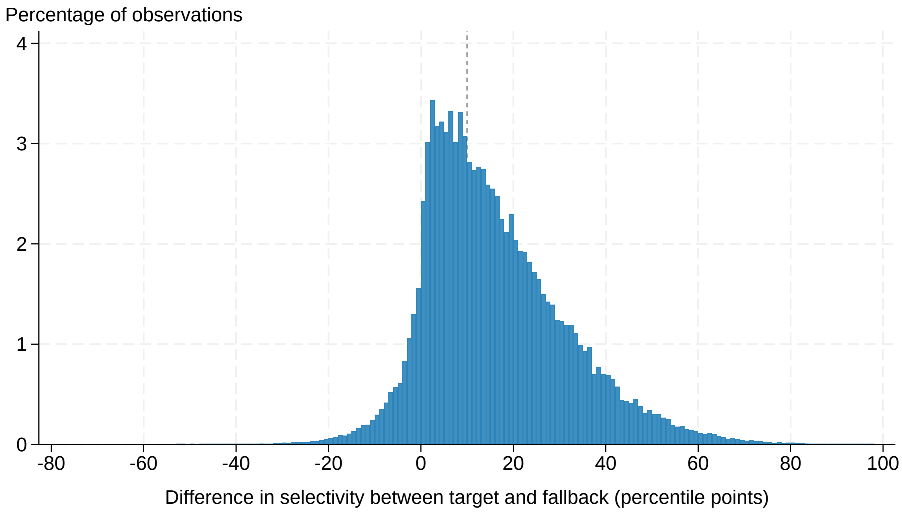
Table A.11: Effect on university degree completion – heterogeneous effects by financial aid

	First program enrolled			Another program	
	Graduated (in ≤ 9 yrs.)	Still enrolled (after 9 yrs.)	Dropped out	Enrolled in another program	Graduated in ≤ 9 yrs. (another program)
Panel A: Has financial aid					
RD Estimate	-0.029***	0.002	0.027***	0.026***	0.003
	(0.010)	(0.004)	(0.010)	(0.010)	(0.007)
Dep. variable mean	0.486	0.041	0.473	0.303	0.127
Observations	134,164	134,164	134,164	134,164	134,164
Obs. within bandwidth	74701	74701	74701	74701	74701
Panel B: Does not have financial aid					
RD Estimate	-0.019	-0.009*	0.028**	0.021*	0.012
	(0.012)	(0.005)	(0.012)	(0.011)	(0.009)
Dep. variable mean	0.482	0.046	0.472	0.326	0.147
Observations	111,495	111,495	111,495	111,495	111,495
Obs. within bandwidth	58812	58812	58812	58812	58812

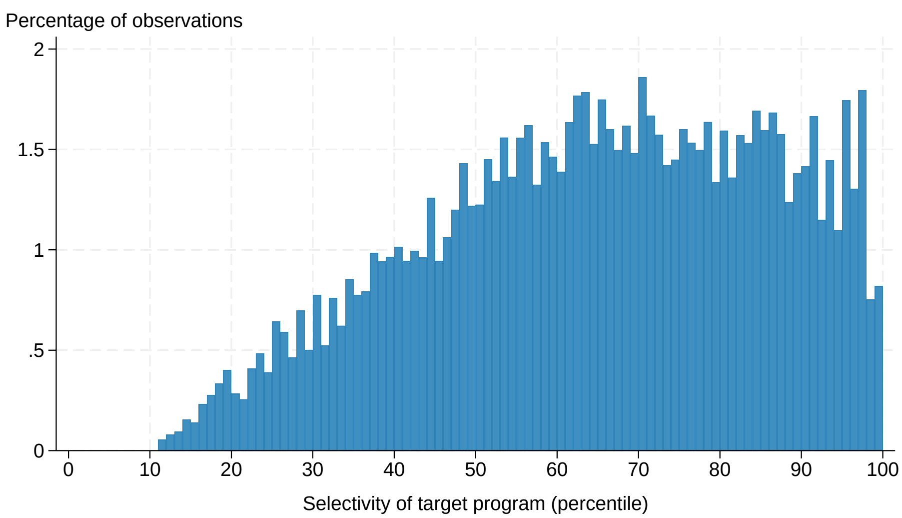
Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students who have (do not have) financial aid in the following categories: BNM, BJGM, BBIC, BPV or FSCU. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over a bandwidth of 25 points at each side of the cutoff. The dependent variable in column 1 is a dummy for whether the student obtained a university degree from the first program they enrolled in, for the nine-year period after applying to university. The dependent variable in column 2 is a dummy for whether the student is still enrolled in that program after nine years, and the dependent variable in column 3 is a dummy for whether the student dropped out of that program. The dependent variable in column 4 is a dummy for whether the student enrolled in another university program, and the dependent variable in column 5 is a dummy for whether the student obtained a university degree from any program in the 9 year period after taking the PSU. Standard errors clustered at the student level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure A.1: Selectivity of target and fallback programs

(a) Distribution of selectivity difference between target and fallback

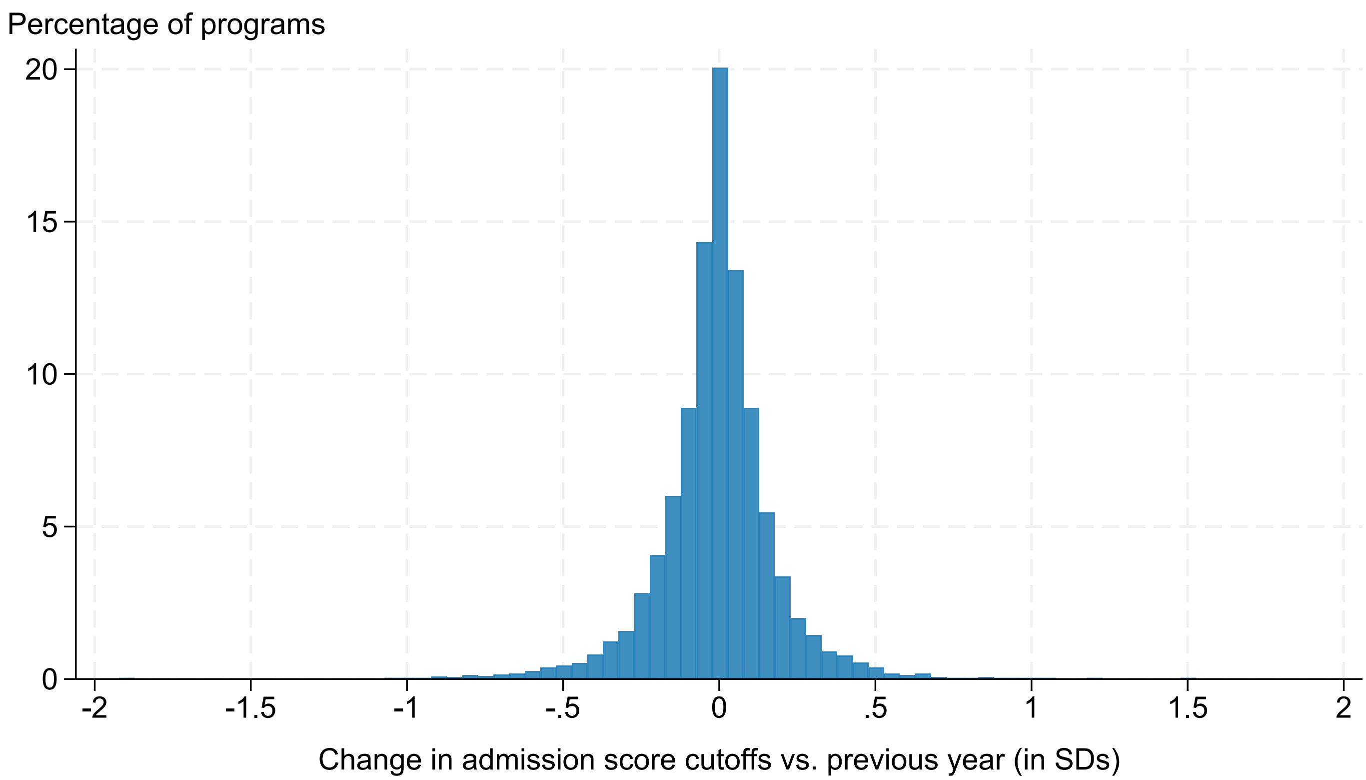


(b) Distribution of selectivity of the target programs in our estimation sample



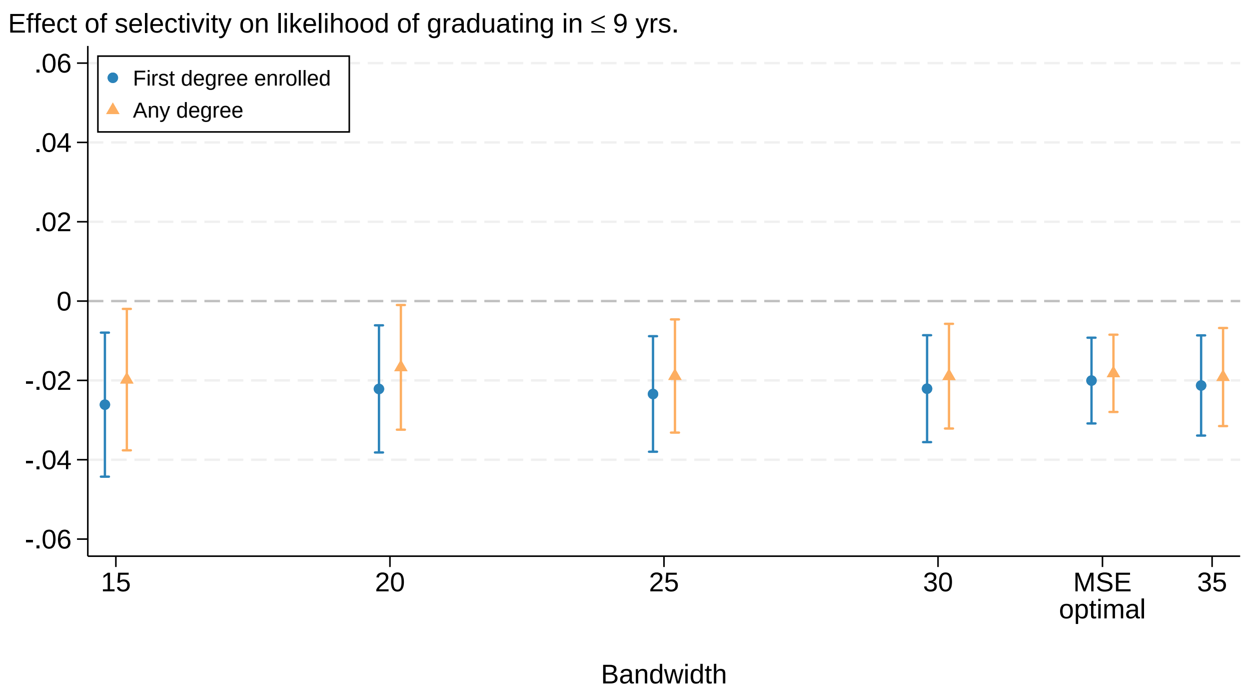
Notes: The figure in Panel A plots the distribution of the difference in selectivity (in percentile points) between the target and fallback programs in our sample, prior to excluding observations with less than a 10 percentile point difference in selectivity, or with a greater selectivity in the fallback than the target program. The figure in Panel B plots the distribution of the selectivity of the target programs in our sample, after making the aforementioned restrictions.

Figure A.2: Distribution of changes in admission score cutoffs



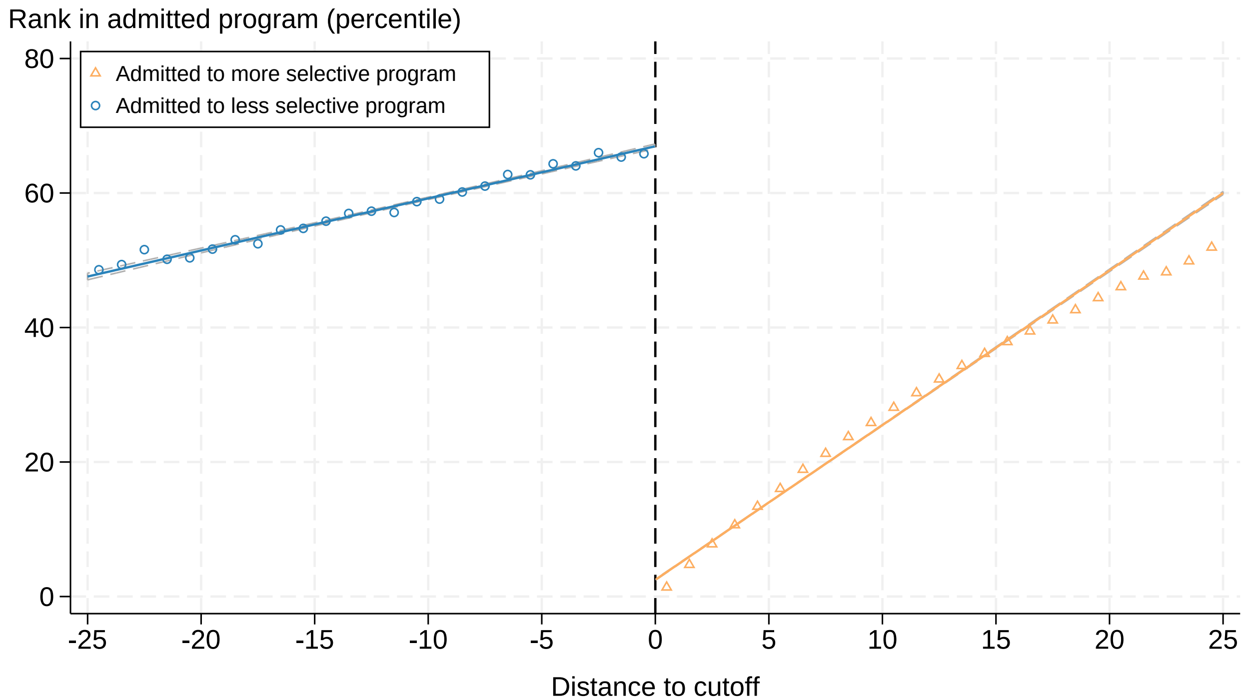
Notes: This figure plots the distribution of the change in admission score cutoffs with respect to the previous year (as a share of the PSU standard deviation) for oversubscribed SUA programs in 2007-2015.

Figure A.3: Effect on university degree completion – robustness to changes in bandwidth



Notes: This figure presents the coefficient and 95% confidence interval of our RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program using different estimation bandwidths. The circular and triangular markers plot the coefficients for estimations where the dependent variables are dummies for whether, in the nine year period after applying to university, the student obtained a university degree from the first program they enrolled in or any university program, respectively. We estimate these regressions using a linear polynomial of the running variable and a triangular kernel, over the bandwidth specified in the x-axis. We cluster the standard errors at the student level.

Figure A.4: Effect on ordinal rank in admitted program



Notes: This figure plots the relationship between the student's ordinal rank in the program he/she was admitted to in the first round and the distance to the admission score cutoff of this program. Dots represent the average outcome variable in equally spaced bins. The solid lines depict a linear fit for regressions conducted on a 25-point bandwidth at each side of the cutoff using a triangular kernel; the dashed lines depict their 95% confidence intervals, with standard errors clustered at the student level.

B Cost-benefit Analysis

This appendix presents a cost-benefit exercise comparing the expected net present value of enrolling in a more selective target program with that of enrolling in the student's less selective fallback program.

B.1 Setup

Students enroll in university at age a_0. Let $p \in \{F, T\}$ index a university program, where F denotes the fallback program and T denotes the target program. Students pay an annual tuition of τ_p at the beginning of every academic year in which they remain enrolled. Let ϕ_p denote the probability of graduating from program p. Both programs are assumed to last D years, while students who do not graduate are assumed to leave after d years.

Graduates are assumed to enter the labor market immediately after completing the program, and earn an annual wage of w_p. For simplicity, students who leave without graduating are assumed to enter the labor market immediately after dropping out, earning W, regardless of what program they drop out from. Wages for graduates and dropouts have an annual wage-real growth rate of g. Everyone works until retirement age A.

Finally, let r denote the annual discount rate. The expected net present value of enrolling in program p is:

$$NPV_p = \phi_p \left[-\sum_{j=0}^{D-1} \frac{\tau_p}{(1+r)^j} + \sum_{k=0}^{A-a_0-D-1} \frac{w_p(1+g)^k}{(1+r)^{D+k}} \right] + (1-\phi_p) \left[-\sum_{j=0}^{d-1} \frac{\tau_p}{(1+r)^j} + \sum_{k=0}^{A-a_0-d-1} \frac{W(1+g)^k}{(1+r)^{d+k}} \right]$$

The first term corresponds to the case in which the student graduates from program p. In this case, the student pays tuition for D years and begins earning the graduate wage w_p immediately after completing the program. The second term corresponds to the case in which the student leaves the program without graduating. In this case, the student pays tuition for d years and begins earning W immediately after dropping out.

B.2 Parameterization

We assume that students enroll in university at age 18 and retire upon turning age 60. For simplicity, we assume that both target and fallback programs are assumed to last five years, while students who do not graduate are assumed to leave after two years. Under these assumptions, graduates enter the labor market at age 23 and work for 37 years, whereas students who leave without graduating enter the labor market at age 20 and work for 40 years.

Annual tuition is 4.036 million Chilean pesos (CLP) of 2024 for fallback programs and 4.405 million CLP for target programs. These values are obtained from the average tuition of programs immediately to the left and right of the admission cutoff, respectively (see Appendix Table A.7).

The fallback-program graduation probability is set equal to the estimated graduation rate from the first program students enroll in immediately to the left of the admission cutoff, which is 0.483 (see Table 2). Our regression discontinuity estimates indicate that admission to the more selective target program reduces the probability of graduating from the initial program by 2.3 percentage points; therefore, the probability of graduating from the target program is 0.460.

We assume that wages grow at an annual rate of 5% for both graduates and students who leave university without obtaining a degree, following Mountjoy (2026). We assume that dropouts earn the minimum wage upon entering the labor market. To obtain the average salary of fallback-program graduates, we use data from MiFuturo, which reports the average salaries of graduates of different programs four years after graduation.[1] We were able to match more than 78% of the fallback programs in our sample. Using annualized gross wages in CLP of 2024, we find that for programs immediately to the left of the cutoff, the annual earnings of graduates four years after graduation is 17.2 million CLP. Assuming that wages grow at an annual growth rate of 5%, this implies that the average annual wages upon graduation from fallback-program graduates are 14.166 million CLP.

Finally, we use an annual discount rate of 3%. Table B.1 below summarizes the parameter values used in the analysis.

[1]MiFuturo is a website that belongs to the Subsecretary of Higher Education, which shows statistics on wages and employability of graduates of different programs. More details available in https://www.mifuturo.cl/.

Table B.1: Parameters used in the cost-benefit analysis

Parameter	Description	Value
a_0	Age at university enrollment	18
A	Retirement age	60
D	Program duration	5 years
d	Years enrolled before dropout	2 years
τ_F	Annual tuition in fallback program	4.036
τ_T	Annual tuition in target program	4.405
ϕ_F	Probability of graduating from fallback program	0.483
ϕ_T	Probability of graduating from target program	0.460
w_F	Annual wage of fallback-program graduates at graduation	14.166
W	Annual starting wage after dropping out	6
g	Annual wage-growth rate	5%
r	Annual discount rate	3%

Notes: Monetary amounts are expressed in millions of 2024 Chilean pesos.

B.3 Expected Net Present Values

Replacing these values into the above equation, the expected net present value of enrolling in the fallback program expressed in millions of CLP of 2024 is:

$$NPV_F = 0.483\left[-\sum_{j=0}^{4}\frac{4.036}{(1.03)^j}+\sum_{k=0}^{36}\frac{14.166(1.05)^k}{(1.03)^{5+k}}\right]+0.517\left[-\sum_{j=0}^{1}\frac{4.036}{(1.03)^j}+\sum_{k=0}^{39}\frac{6(1.05)^k}{(1.03)^{2+k}}\right]$$

For the target program, assuming a proportional wage premium of target-program graduates relative to fallback-program graduates of x, the corresponding expected net present value is:

$$NPV_T = 0.460\left[-\sum_{j=0}^{4}\frac{4.405}{(1.03)^j}+\sum_{k=0}^{36}\frac{14.166(1+x)(1.05)^k}{(1.03)^{5+k}}\right]+0.540\left[-\sum_{j=0}^{1}\frac{4.405}{(1.03)^j}+\sum_{k=0}^{39}\frac{6(1.05)^k}{(1.03)^{2+k}}\right]$$

Evaluating these expressions yields:

$$NPV_F = 476.350,$$
$$NPV_T = 468.157 + 300.247x$$

Therefore, the expected net present values of the target and fallback programs are equal when the target-program wage premium, x, is 2.73%.