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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, 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 and negative peer effects, 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, or if instructors adjust their teaching or grading to match the ability level of the typical student. 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 aspect of the Chilean system is that it allows us to identify students' next-choice option in case they are marginally denied admission to this program—their fallback program. 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 admission threshold in their fallback option. This ensures that the counterfactual option is admission to a relatively less selective university program,

[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 question.

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. 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 several potential mechanisms through which crossing the admission threshold for a more selective program may result in lower graduation rates. First, more selective programs typically have higher academic rigor, which may lead to lower graduation rates for students at the margin, who struggle to meet the program's demands. Second, students marginally admitted to more selective programs have more able peers, potentially leading to worse outcomes if instructors adapt their teaching to higher-ability students or grade on a curve (de Roux and Riehl, 2022). Finally, 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). We repeat the estimation for applicants at the margin of admission between 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

[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 and not being admitted to any university.

and peer ability. We find that having a lower ordinal rank does not lead to worse graduation outcomes. Finally, we find that the effect of selectivity is mostly driven by students admitted to programs with a larger skill gap between the median and the last admitted student. These results suggest that the negative effects of selectivity that we uncover are driven by academic rigor and/or other peer effects that negatively affect marginally accepted students.

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 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] Some of these studies focus on lower-ability students, who are at the margin of admission to relatively nonselective 4-year colleges (e.g., Zimmerman, 2014 and Goodman, Hurwitz and Smith, 2017). Since many marginally admitted students in these contexts would otherwise attend a 2-year college or not enroll at all, the increased likelihood of earning a bachelor's degree is at least partly mechanical.[5] Also in the U.S., Cohodes and Goodman (2014) focus on students who are at the margin of attending universities 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 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 have

[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.

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, 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. Second, we provide evidence on the effect of selectivity for a broad set of programs and consider students across a wide range of ability levels. Third, we focus on students for whom the counterfactual is admission to a relatively less selective university program, thus minimizing the risk that our findings are driven by changes in the likelihood of attending a university program at the cutoff. Our results question the prevailing view in the literature by showing that students marginally admitted to more selective programs are less likely to obtain a university degree.

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

[6] For example, Zafar (2011) shows that low-performing students at Northeastern University adjust to learning about their chances of academic success by switching to a less demanding major within the same university. 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).

analysis period, all public universities (25 state and non-state institutions) participated in a centralized admission system (*Sistema 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, and 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 seats available. Students with a score lower than the last selected student are placed on a waitlist. In a second round, seats declined by admitted applicants are assigned by merit order to waitlisted applicants. Given this application process, cutoff scores vary yearly, creating uncertainty about students' ability to predict their acceptance to 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

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

students: 68% of those attending public institutions benefited from public loans and/or 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 parent's

[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.

educational level. For each program the student applied to, we have information on 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 in 2007-2023. This includes not only SUA programs but all other programs in higher education. Each dataset has unique student identifiers, allowing us to merge the two data sets 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 within 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

[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 to prevent a violation of the independence restriction since students who are enrolled in university are, by definition, more likely to complete a university degree. Furthermore, 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).

they would get into if narrowly denied admission to the target program; it is the most 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 (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 belong 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 choices as well as between their second and third choices, 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. Student B's relevant target program is their third choice, as the first and second options were discarded due to minimal selectivity differences with their fallback options. 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 fourth 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 $\beta_1$ 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 (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 student's 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 within 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 is smaller (1.2 percentage point) and not statistically significant at conventional levels. In contrast, for lower-income students, the effect is as large as the decline observed 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 are studying with government scholarships or grants, whereas

[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. While 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), they are at the margin of being admitted to programs with lower selectivity (percentile 60 vs. 68, on average).

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 from 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 show that the negative effects of marginal admission to a relatively more selective program are disproportionately borne by lower-income students and students with lower 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 percentage points), there are no differences in the cutoff in the likelihood of being admitted

[23] The data on government financial aid is available from 2008, 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 grants 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.

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 obtain data on the average salaries of graduates of each program from MiFuturo, which reports gross wages four years after graduation.[26] We were able to match more than 85% of the target programs and 78% of the fallback programs. Using annualized gross wages in Chilean pesos (CLP) of 2024, we find that the wage difference at the cutoff between target and fallback options is 1.662 million CLP—a 9.7% increase over the 17.219 million CLP earned by graduates of fallback programs just to the left of the cutoff, as shown in Appendix Table A.9.

We compare students' outcomes under both programs. The return of attending either the target or fallback program is the earnings after graduation, net of tuition costs and weighted by the probability of graduating, plus the earnings students would have

[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]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/.

obtained had they dropped out—also weighted by the probability of not graduating—minus the total wages students would have earned both during their college years and after had they not enrolled in university. For simplicity, we assume that the wages of graduates are constant during the initial period after graduation. We also assume that a student would obtain the same wage after dropping out from their target of fallback program. Thus, after graduation, the expected benefit of attending the target program $t$ instead of the fallback programme $f$ would be the following:

$$(Wages_t - Tuition_t) \times Prob.Graduating_t - (Wages_f - Tuition_f) \times Prob.Graduating_f \quad (3)$$

, where $Wages_j$ are the accumulated wages of program $j$ in the post-graduation period. We calculate this for each year after graduation using the results of our estimations. Target programs are 0.369 million CLP more expensive per year (relative to a mean tuition of 4.036 million CLP in fallback programs), as seen in Appendix Table A.7. Furthermore, target programs last 0.343 extra semesters (on top of the 9.794 semesters of fallback programs), making the total tuition of target programs 2.56 million CLP higher (in CLP of 2024). Finally, the probability of graduating from the fallback program is 0.483, whereas it is 2.3 percentage points lower for the target program (Table 2).

Appendix Figure A.4 plots the value of $(Wages_j - Tuition_j) \times Prob.Graduating_j$ for the first six years after graduation, both for the target and fallback programs. While the accumulated benefit of the fallback program is larger than that of the target in the first year (by 0.356 million CLP), the higher wage for graduates of the target program more than compensate for the lower graduation rates by the following year. After six years, students who attended their target program can expect to receive an extra 1.487 million CLP (approximately 1500 dollars) over students who attended their fallback options, net of tuition costs.[27] For students admitted to the fallback program to be better off six years after graduation, the likelihood of graduating would have to fall by more than 3.9 percentage points. Thus, we find that despite the lower likelihood of graduation, it remains ex-ante advantageous for students to enroll in the more selective target program.

[27] The accumulated six-year post-graduation wages for the target program are 113.29 million CLP, whereas the total cost of these programs is 22.33 million CLP, and the probability of graduating is 0.460. The accumulated six-year post-graduation wages for the fallback program are 103.31 million CLP, whereas the total cost of these programs is 19.76 million CLP, and the probability of graduating is 0.483. Therefore, the benefit of attending the target program instead of the fallback is (113.29-22.33)*0.460-(103.31-19.76)*0.483, which equals 1.487million CLP.

# 5 Why does selectivity lead to lower degree completion?

There are several potential mechanisms through which crossing the admission threshold for 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.[28] Second, students marginally admitted to more selective programs will have more able peers than those admitted to less selective programs. Although having better peers could result in positive learning externalities (Sacerdote, 2011), it could also lead to worse outcomes if instructors adapt their teaching methods depending on their students' ability, or grade on a curve (de Roux and Riehl, 2022). Third, 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.5). 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).[29] 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 or peer characteristics by re-estimating our model for the sample of students at the margin of admission between two programs with similar selectivity levels.[30] More specifically, we focus on cases where the difference in selectivity between the target and fallback programs is smaller 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.

[28]It is not obvious that more selective programs are more academically rigorous. In India, 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.

[29]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.

[30]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 quality.

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).

Another way of assessing the relative importance of academic rigor and negative peer effects–such as teachers grading on a curve or adjusting their instruction to their students' ability–is by leveraging the variation in our sample in the skill gap between the median and the last admitted student. As shown in Appendix Figure A.6, there is substantial variation across target programs in this gap, measured by the difference between the median math-language PSU score and the PSU score of the last admitted student. A larger gap implies that marginally admitted students are entering programs where the typical student has a higher skill level. In such environments, academic rigor may be higher, as course content and pace are likely aligned with the median student. Furthermore, if grading is done on a curve, students at the lower end of the skill distribution–such as the last admitted ones–are more likely to receive lower grades relative to their peers. We perform our main estimations by splitting the sample based on whether the target program for which the student is at the margin of admission is above or below the sample median. Notably, this measure is distinct from program selectivity, as the two metrics are only weakly correlated (Appendix Figure A.7).[31] We present our results in Appendix Table A.11.

Consistent with academic rigor and peer effects playing an important role, we find that the negative effect on the likelihood of graduating from the first program is driven by students marginally admitted to programs with a large skill gap among students (Panel A, column 1). Specifically, marginal admission to a more selective program reduces the likelihood of graduating from the first program by 3.2 percentage points in cases with a significant skill gap (statistically significant at the 1% level), compared to a statistically insignificant effect of 1.7 percentage points for students admitted to a more selective program with a skill gap below the median. Overall, our results suggest that the negative effects of selectivity we observe are likely driven by higher academic rigor or negative peer effects, with ordinal rank playing no role in our context.

[31] For the majority of our sample (93%), target program selectivity is above the 30$^{\text{th}}$ percentile (Panel B of Appendix Figure A.1); above this point, there is a weak correlation between the skill gap of admitted students and program selectivity (Appendix Figure A.7).

## 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 rigor and potential negative peer effects of more selective programs, rather than to 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, 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 shows that it remains ex-ante advantageous for marginal students to enroll in more selective programs, due to the substantial wage gains for those who graduate. To fully realize these benefits, universities should enhance their support structures, thus helping students navigate and succeed in these settings.

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# 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 that 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 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 |

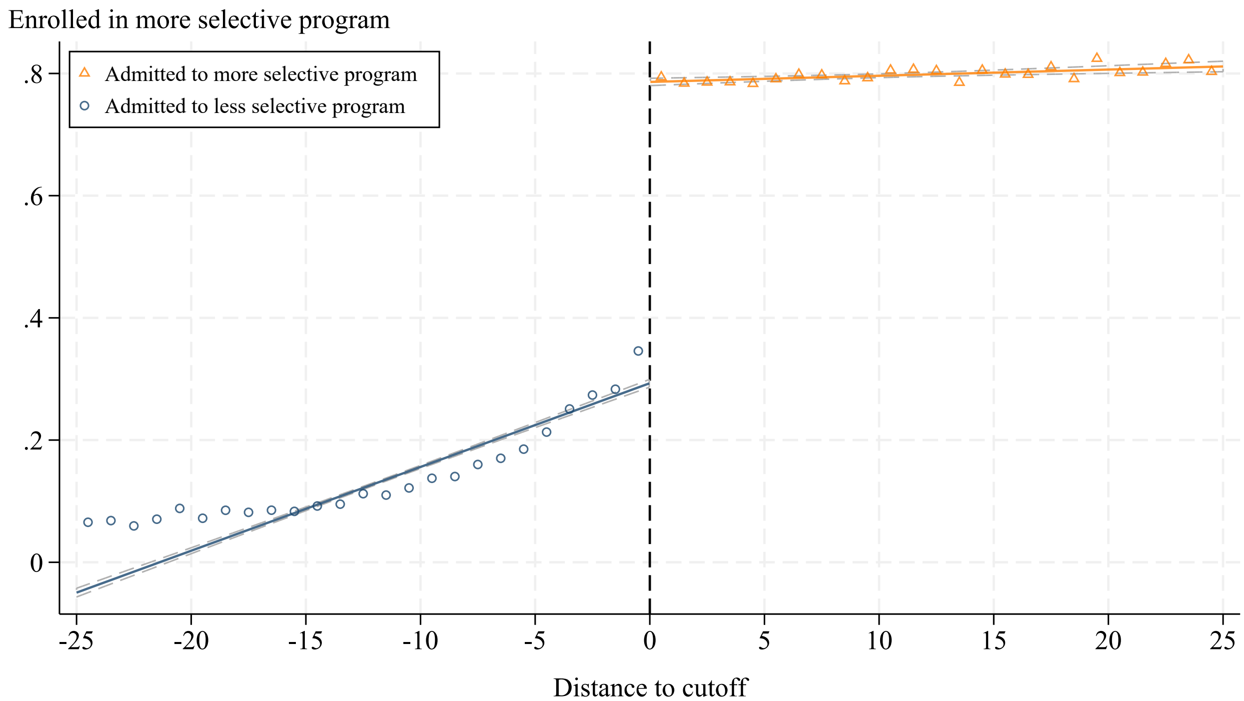
Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students that are below (above) the sample median in their cohort in terms of average math and language PSU scores. We 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 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 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 |

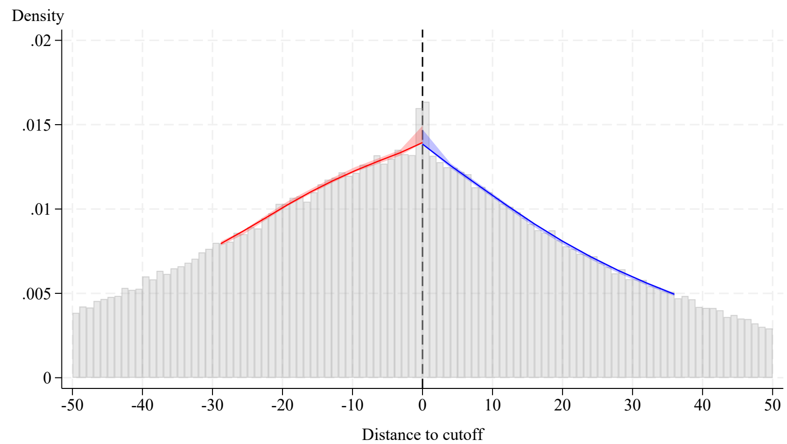
Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program. The sample in Panel A (B) is composed of students whose target program is above (below) the sample median in terms of our measure of selectivity. We estimate these 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%.

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

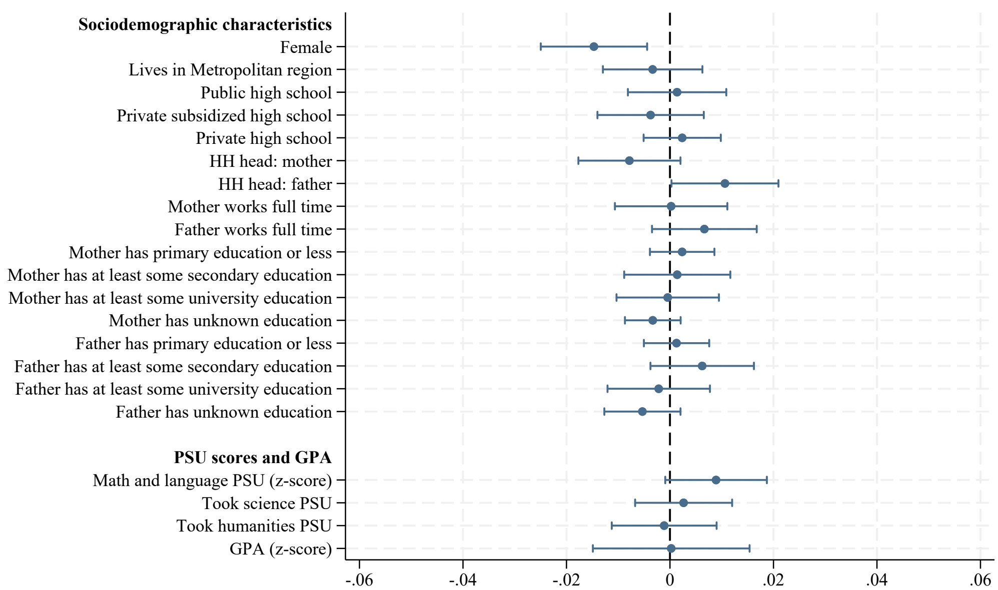



Notes: This figure plots the relationship between the likelihood of enrolling in the relatively more selective target program and the distance to the admission score cutoff of this program. The outcome variable is a dummy variable taking the value of 1 if the student enrolled in this program in the same 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



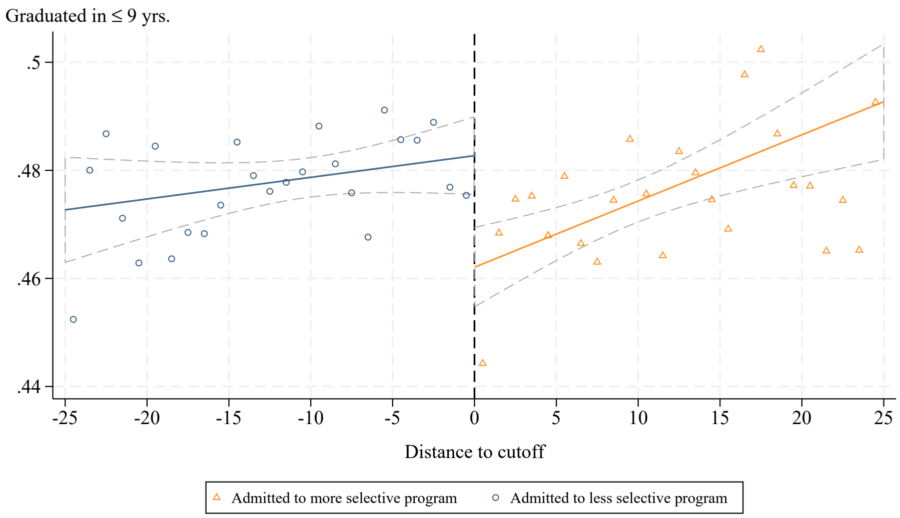

(a) Density of the running variable



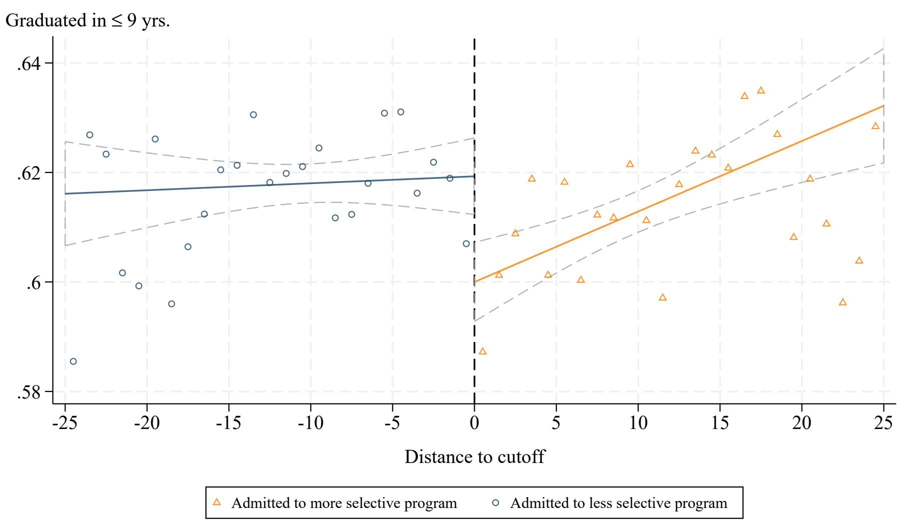

(b) Covariate balance at the cutoff

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



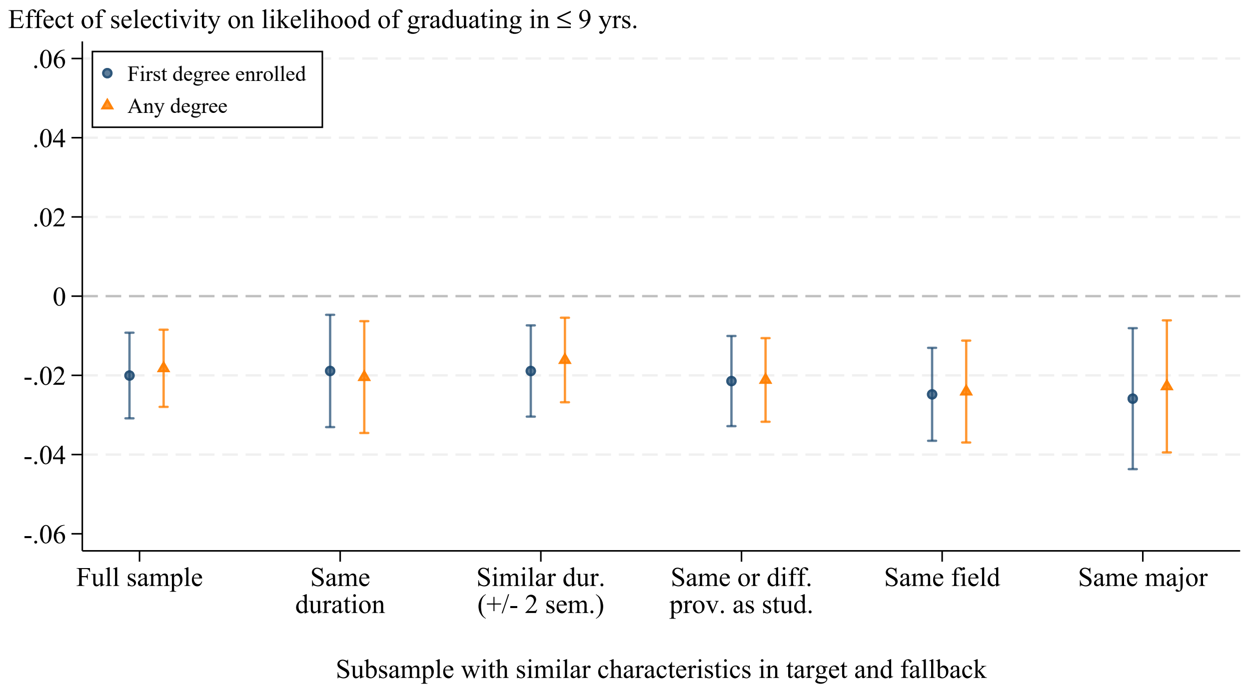

(a) First program enrolled




(b) Any program

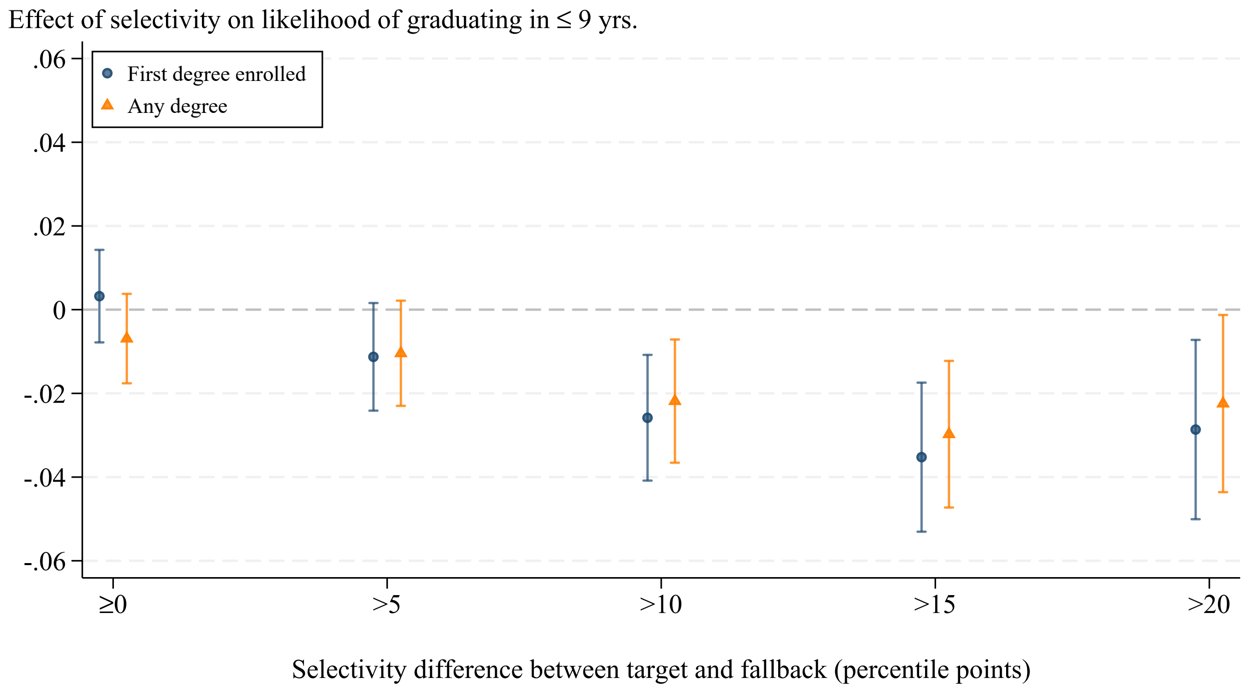
Notes: These figures plot the relationship between the likelihood of graduating and the distance to the admission score cutoff for the target program. The outcome variables in Panel A and B are dummies for whether, in the nine year period after applying to university, the student obtained a university 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 in 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

## Appendix 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 de Valparaiso | 74 | -20.60 | Waitlisted |
| B | 2 | Law | Universidad de Talca | 75 | -13.62 | Waitlisted |
| B | 3 | Law | Universidad Católica del Norte | 68 | 4.85 | Admitted in 1st round |
| B | 4 | Law | Universidad de Antofagasta | 32 | 56.30 | - |

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

| | Selectivity diff ≥ 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 that 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 that 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 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. 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 million 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 wages 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 wages four years after graduation, 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 |

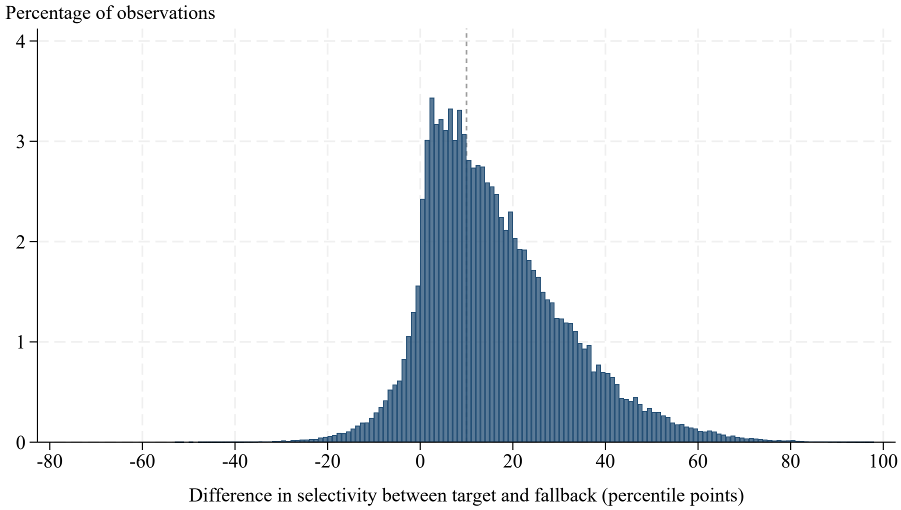
Notes: This table presents RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more preferred program. We limit the sample to observations for which the target and fallback program have a difference in selectivity smaller than 5 percentile points. We estimate these 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 and time to graduation – heterogeneous effects by skill gap between median and last admitted student

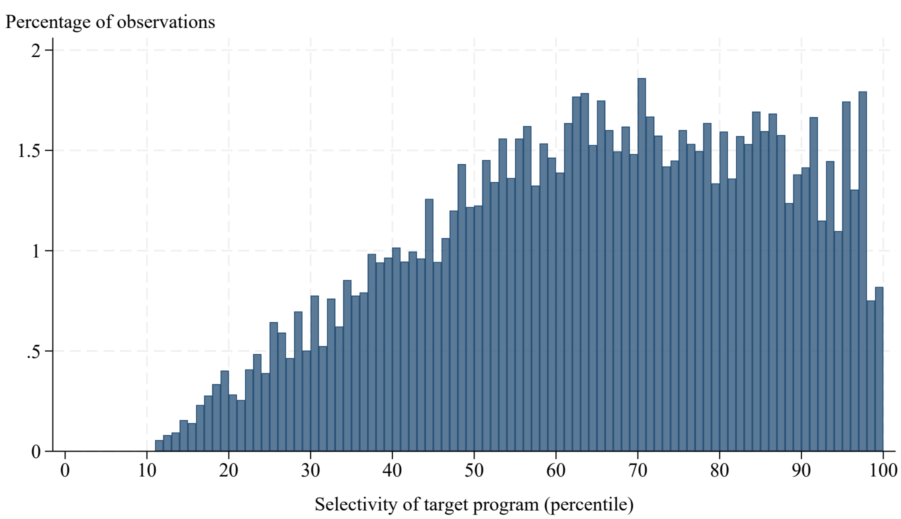
| | Graduated in 9 years | | Yrs. until completion | |
|---|---|---|---|---|
| | First program | Any program | First program | Any program |
| *Panel A: Above median skill gap* | | | | |
| RD Estimate | -0.032*** | -0.027** | 0.146*** | 0.172*** |
| | (0.010) | (0.010) | (0.038) | (0.034) |
| Dep. variable mean | 0.458 | 0.597 | 6.788 | 6.982 |
| Observations | 137,187 | 137,187 | 61,559 | 80,724 |
| Obs. within bandwidth | 75164 | 75164 | 33446 | 44197 |
| *Panel B: Below median skill gap* | | | | |
| RD Estimate | -0.017 | -0.013 | 0.044 | 0.061* |
| | (0.011) | (0.010) | (0.036) | (0.033) |
| Dep. variable mean | 0.509 | 0.643 | 6.696 | 6.900 |
| Observations | 134,696 | 134,696 | 68,487 | 86,257 |
| Obs. within bandwidth | 73740 | 73740 | 37421 | 47307 |

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 the gap between the math and language PSU score of the median and last admitted student. 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 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 A.1: Selectivity of target and fallback programs



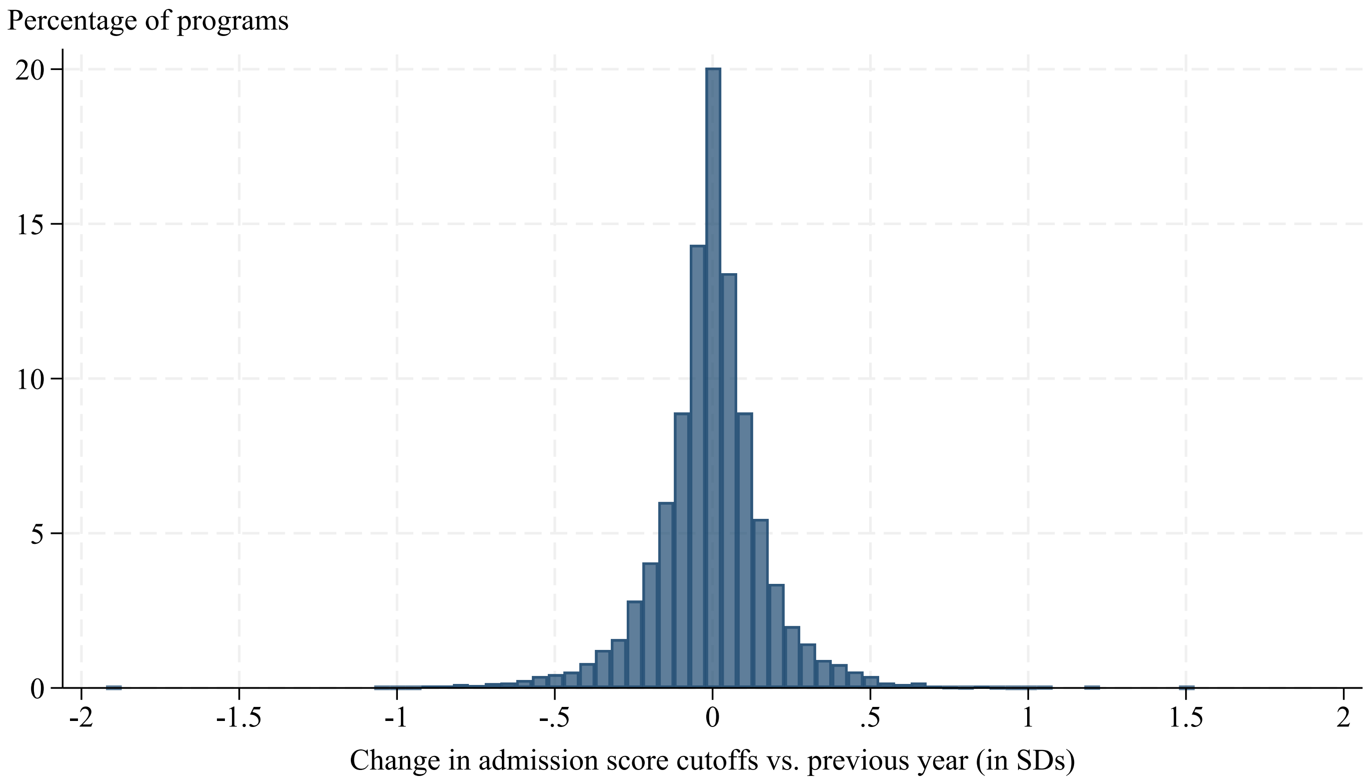

(a) Distribution of selectivity difference between target and fallback




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

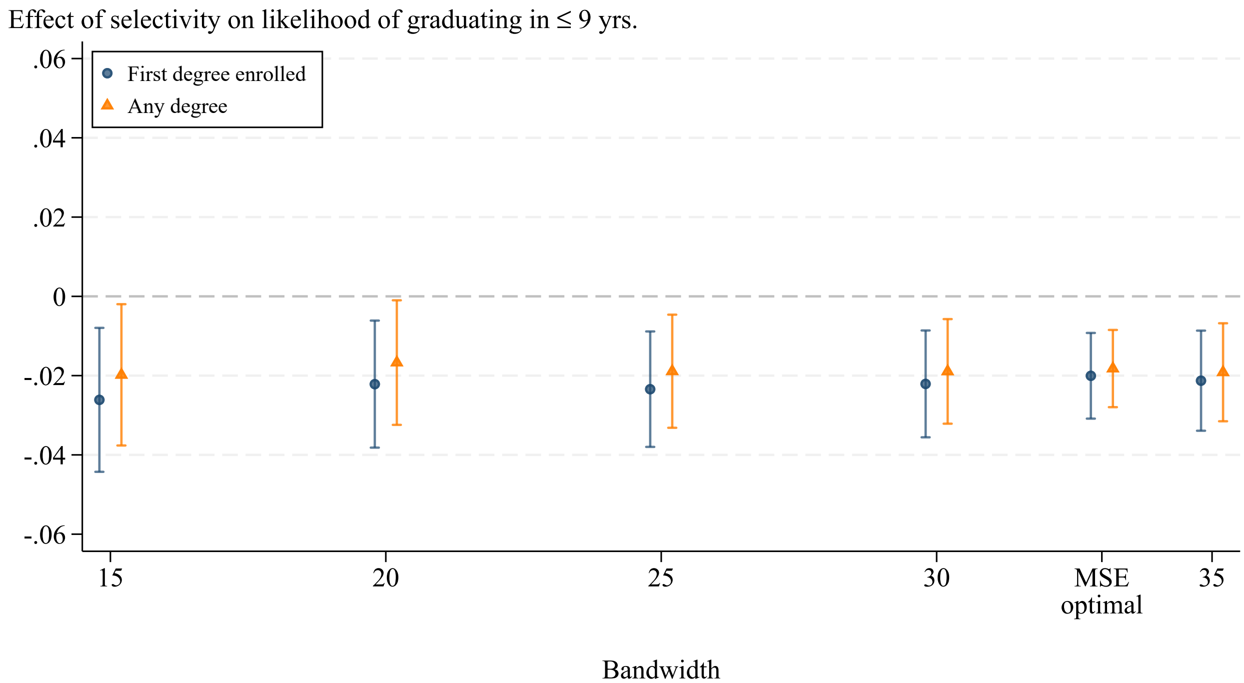
Notes: The figure in Panel A plots the distribution of the difference in selectivity (in percentile points) between the target and fallback programs in our sample, prior to excluding observations with less than a 10 percentile point difference in selectivity, or with a greater selectivity in the fallback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



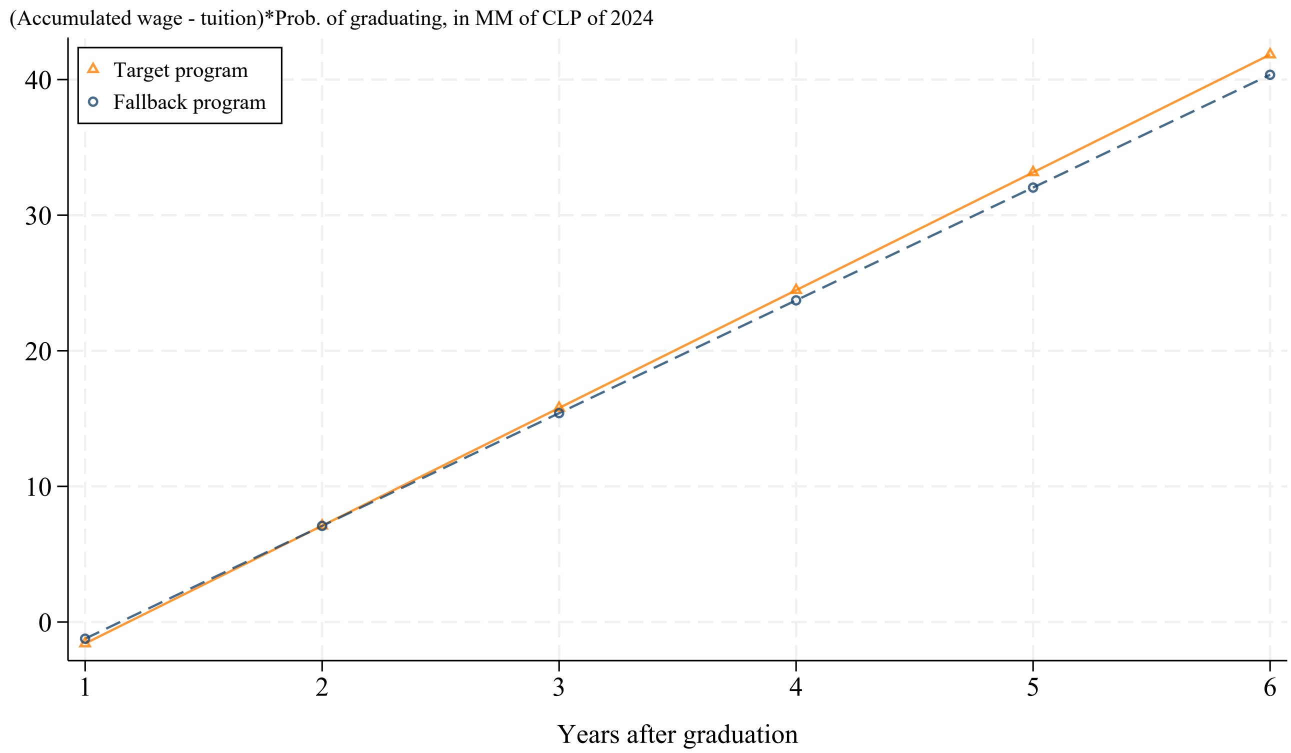

Notes: This figure plots the distribution of the change in admission score cutoffs with respect to the previous year (as a share of the PSU standard deviation) for oversubscribed SUA programs in 2007-2015.

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



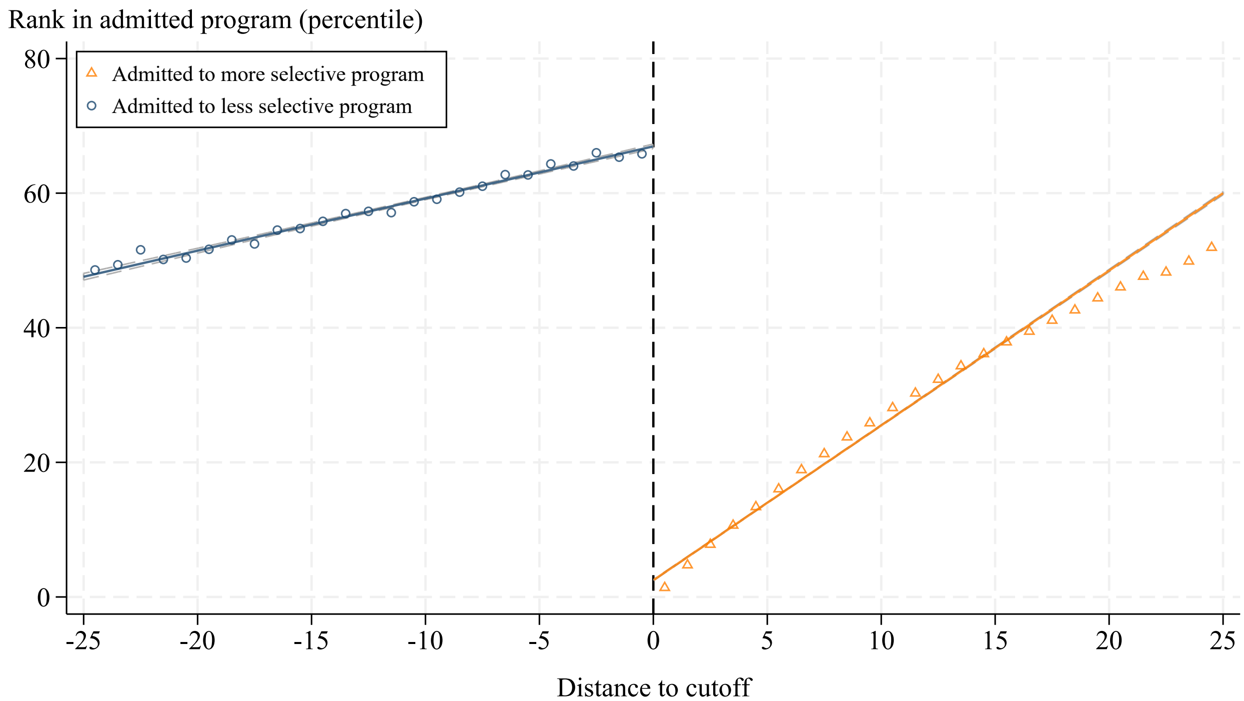

Notes: This figure presents the coefficient and 95% confidence interval of our RD estimates (bias-corrected with robust standard errors) of the effect of admission to a more selective program using different estimation bandwidths. The circular and triangular markers plot the coefficients for estimations 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: Cost-benefit analysis



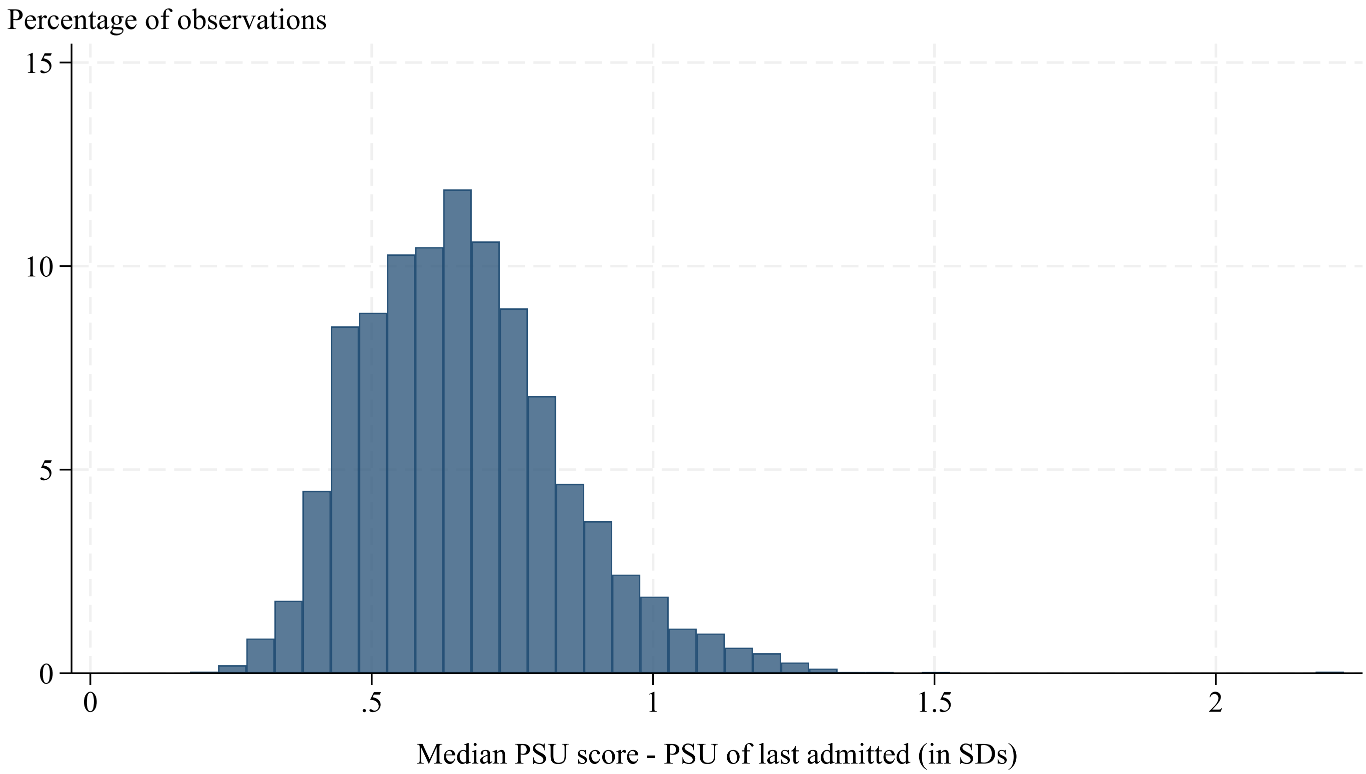

Notes: This figure plots, for the target and fallback programs at the cutoff, the difference between the accumulated wage (in MM of CLP of 2024) and total tuition, weighted by the probability of graduating, for the four year post-graduation period.

Figure A.5: Effect on ordinal rank in admitted program



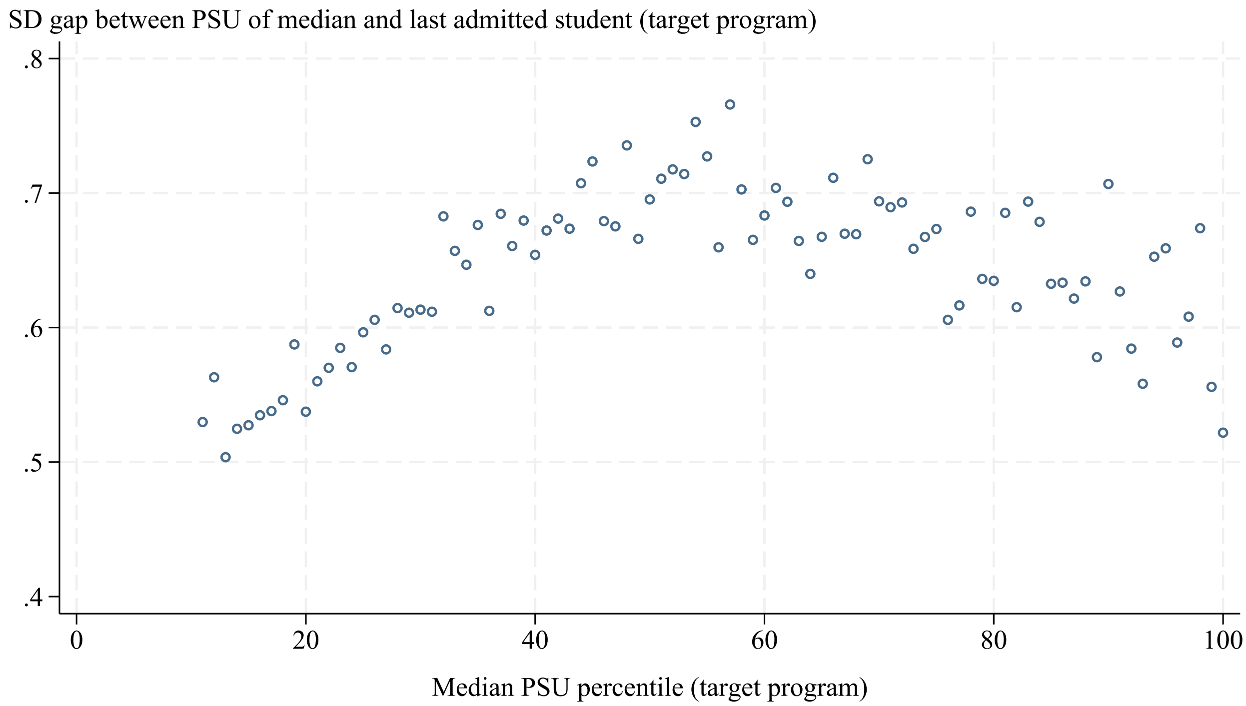

Notes: This figure plots the relationship between the student's ordinal rank in the program he/she was admitted to in the first round and the distance to the admission score cutoff of this program. Dots represent the average outcome variable in equally spaced bins. The solid lines depict a linear fit 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.

Figure A.6: Distribution of gap between the PSU of the median and last admitted student (target program)




Notes: This figure plots the distribution of the difference in average math and language PSU scores of the median and last admitted student for the target programs in our sample, expressed in standard deviations of the PSU score.

Figure A.7: Correlation between program selectivity and gap between median PSU and PSU of last admitted student (target program)




Notes: This figure plots the relationship between the median PSU percentile and the difference in math and language PSU scores between the median and the last admitted student (in standard deviations of the PSU score) for the target programs in our sample. For each median PSU percentile, we plot the average of the dependent variable.