Grants vs. Loans: the Role of Financial Aid in College Major Choice*

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Abstract

We analyse whether financing higher education through student loans or grants affects the college major choices of students in Chile, where either type of financing is allocated based on a standardised test. Students who are marginally eligible for grants are more likely to enrol in high-paying fields such as STEM. Complementing the reduced form result, we estimate a discrete choice model on data for narrowly defined higher education programmes. The results indicate that, holding other programme characteristics constant, grant recipients place a higher value on fields with high earnings growth potential, while being less concerned about a lower graduation probability.

Keywords: major choice, financial aid, education policy, regression-discontinuity-design

JEL classification numbers: H52, H81, I22, I28

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1 Introduction

College majors differ substantially in aspects such as expected labour market earnings, employment probabilities, and difficulty of degree completion. For instance, contrasting high-return majors with low-return majors reveals differences in earnings comparable to the overall college wage premium (Altonji *et al.*, 2012). The question of which major to enrol in is consequently a significant investment decision for anyone pursuing higher education.[1]

In this paper, we investigate how higher education financing and financial aid policies shape individual college major choices. In the presence of tuition fees, prospective students financing their higher education with either student loans or grants face vastly different post-university debt levels. Concerns about the repayment of loans might encourage students to choose areas of study with better expected labour market outcomes. At the same time, they might disincentivise the choice of fields in which degree completion is either less likely (dropout) or takes longer to achieve. Under this alternative hypothesis, grants could provide insurance against study-related uncertainty. If degree completion uncertainty and favourable labour market prospects are correlated at the college major level, it is not trivial to establish a theoretical prediction of how replacing student loans with grants should impact the choice of a given major. We contribute to the understanding of individual college major choices by not only providing causal evidence on shifts in the distribution of college major choices between students financed by grants or loans but also by disentangling the relative contribution of programme-specific characteristics in shaping these choices.

The laboratory for our study is the higher education system of Chile, where students can either borrow up to a reference tuition from a state-backed student loan system or receive the same amount in the form of a grant. Access to either student loans or grants is determined fully by a combination of family income requirements and the result of a centralised admissions test, the *Prueba de Selección Universitaria (PSU)*. Conditional on income, a sharp test score threshold allows us to identify local exogenous variation in eligibility for either type of financing. During our study period, Chilean universities charge relatively high tuition fees of typically around 50% of yearly median family income per year of study. The need for financial assistance is consequently widespread, and a majority of students apply for financial aid.

Using administrative data on individual-level college enrolment and PSU test results for the

[1] Besides the pure impact on future earnings (Hastings *et al.*, 2013; Kirkeboen *et al.*, 2016; Britton *et al.*, 2022), the choice of a university major naturally also affects other margins. Among others, it has a gender component by preconditioning occupational sorting (Sloane *et al.*, 2021), and it plays a role in determining household-level inequality through assortative mating (Eika *et al.*, 2019).

universe of test-takers in Chile, we follow a regression-discontinuity approach and study changes in college major choices of incoming students around the test-score threshold that permits access to grants. We observe an increased enrolment of 11.5% (2.9 percentage points) in science, technology, engineering, and mathematics (STEM) majors and a 12% (less precisely estimated) increase in the social sciences. Interestingly, the estimates of Hastings *et al.* (2013) point in the direction that both STEM and social science majors offer particularly high economic returns in Chile. More generally, STEM fields are an interesting group of subjects to focus on since – as we show below – they are an example of majors that are characterised by high mean monetary returns and employment probabilities but also by high dropout rates and earnings uncertainty.

The fact that we see increased enrolment in high monetary return fields such as STEM makes it unlikely that more generous financial aid leads students to choose lower return fields on average. To corroborate this finding, we use data from *MiFuturo*, an initiative by the Chilean Ministry of Education, which collects information of past graduates for narrowly defined higher education programmes (major $\times$ institution type, e.g., chemistry at a university or biology at a vocational higher education institution). It allows prospective students to anchor their expectations about programme-specific aspects such as employment probabilities, as well as average earnings (one to five years after graduation) and their spread (10th percentile, median, 90th percentile), ex-ante dropout risk, and average time to degree completion.

We use several of these characteristics as separate outcomes in the regression-discontinuity framework to better characterise students' chosen programmes. Students with access to grants are significantly more likely to enrol in fields that are associated with high earnings and high earnings growth (2.2 and 1.9 percentage points, respectively). At the same time, they are 1.9 percentage points less likely to enrol in fields where the risk of taking longer than the formal study duration to graduate is low. Despite the significantly higher dropout rates in STEM fields (about half a standard deviation above other fields), students with grants are not more likely to pick fields associated with higher dropout rates than students with loans. We show that part of this is explained by a second margin of adjustment: students with grants are more likely to enrol in more prestigious, higher-quality institutions where overall dropout rates are lower. This interplay between institutional quality and dropout rates highlights our notion that a thorough understanding of the link between financial aid and college major choices requires a more nuanced description of majors that goes beyond the comparison of characteristics in isolation.

In a second application of the programme-level information, we take the correlated nature of programme characteristics seriously and estimate a discrete choice model to disentangle their importance conditional on other characteristics. We do so within a narrow bandwidth around the grant eligibility cut-off, merging the discrete choice logic and that of the RD in a multinomial RD approach. The aim is to understand how the valuation of programme characteristics underlying the discrete choice changes between grant and loan recipients at the cut-off.[2]

The results of this exercise indicate that conditionally, students who are marginally eligible for grants are, in fact, less concerned about dropout rates and excessive times until degree completion in their preferred programmes. They also value steeper earnings growth trajectories more positively. Other labour market outcomes such as mean earnings or employment probabilities, on the other hand, are not valued differently by students with access to different types of financial aid. Both grant recipients and loan takers have a strong distaste for programmes with high dropout rates, and both value a steeper earnings growth potential positively. However, having access to grants changes this trade-off significantly. Students with loans are willing to forgo 6.4% of total earnings growth over the first five years after graduation to decrease programme-specific dropout rates by 1%. For grant recipients, the equivalent number is only 3.6%. Our results imply that grants allow students not only to choose higher quality programmes but, conditional on doing so, to be less concerned about dropout risks and instead align their choices with steeper lifetime earnings profiles. Since we define programmes narrowly for the estimation of our choice model, we can additionally include fixed effects for nine more aggregate fields of study and institution types (vocational vs. university). That is, we consider variation in dropout rates between programmes *within* the broader set of STEM degrees and *within* institution types, adjusting for a host of potentially unobserved characteristics.

Contrary to our results, a small literature focusing mostly on sets of U.S. universities finds evidence that financial aid might shift the relative importance of pecuniary and non-pecuniary aspects of college majors for students' choices, thereby increasing enrolment in relatively lower return fields (Rothstein and Rouse, 2011; Stater, 2011; Sjoquist and Winters, 2015a,b; Andrews and Stange, 2019; Boelmann *et al.*, 2024).[3] In recent contemporaneous work, Hampole (2024) argues that these findings partially reflect intertemporal trade-offs: students with a lower debt burden are

[2]In this sense, our approach differs slightly from the small recent literature on multinomial regression discontinuity designs (e.g., Koch and Racine, 2016; Xu, 2017), in which applications are interested in discontinuities in the probability mass of choice options at the cut-off.

[3]An exception is Castleman *et al.* (2018) who find that a need-based grant increased STEM credit completion, albeit not graduation with a STEM degree, among students in Florida. They do, however, restrict their sample to students who either took advanced math classes in high school or passed the threshold for college-math preparedness on the math SAT, thereby explicitly targeting students who would plausibly pursue STEM degrees.

willing to choose fields with lower initial earnings if they offer a steeper earnings growth potential. We complement and extend this literature by explicitly disentangling the influence of many such correlated programme characteristics and their interaction with financial aid, including earnings and earnings growth trajectories. Relying on a discrete choice model, we thereby show that labour market prospects after graduation are only a subset of relevant programme characteristics, which need to be adjusted for in order to appropriately characterise the driving forces behind the effect of financial aid on students' choices. We do find that uncertainty about degree completion and time to graduation are prominent channels in our setting. An additional advantage of the Chilean financial aid setting is that it is harmonised across the entire country and is not specific to individual universities. In combination with administrative records on the universe of financial aid applicants, this allows us to cleanly identify rich shifts in education choices across the entirety of Chilean higher education institutions.

There are at least two key institutional differences between the U.S. and Chile to keep in mind when contrasting our results with previous empirical evidence.[4] First, student loans in Chile have an income-contingent component by default (see Section 2 for details). The alternative to grants is, therefore, a loan system that already provides some insurance against labour market risks, which is typically argued to be a key feature of optimal student loan arrangements (Lochner and Monge-Naranjo, 2016; Britton *et al.*, 2019). For this reason, we might see muted differences between students with either grants or loans in terms of revealed preferences for labour-market characteristics. Second, even income-contingent loans provide limited insurance against study-related risks such as dropout or a long time until degree completion, which is a significant threat in the Chilean context. While in the U.S., switching majors is a common route to avoid college dropout (Arcidiacono, 2004), students in Chile enrol directly in institution-major combinations. Transferring financial aid to another institution or another major within the same institution is possible only in justified cases and at a maximum of once. In fact, in our data, around 70% of first-year students progress to the second year in the same institution-major combination, 10% enrol either in another institution or another major, and 20% drop out of higher education. Following the latter group for nine years after their first enrolment indicates that only one out of five dropouts graduates from higher education at a later point in time.

[4]Our paper is part of a growing series of studies that make use of the institutional setting of Chile's higher education system. Previous papers, for instance, investigate the labour market returns to college over vocational institutions (Bucarey *et al.*, 2020) or to various majors (Hastings *et al.*, 2013), the role of financial aid in the decision to enrol in college (Solís, 2017), to drop out over time (Card and Solís, 2022) and for labour market outcomes (Solís, 2024), as well as the effectiveness of preferential admission policies (Tincani *et al.*, 2023).

Even though, on average, students with grants do not enrol in fields with low graduation rates, our choice model reveals that, keeping other programme characteristics fixed, they are less concerned about dropout rates. We might consequently be concerned that marginally entering students are negatively selected and do not manage to graduate. In light of the opportunity costs involved in higher education investments, this could imply a low-return investment even if grants prevent students from the need to repay loans after dropping out. In a final exercise, we track students around the grant eligibility cut-off throughout their university career. Conditional on enrolling, we find that marginally eligible students are not less likely to graduate successfully than marginally ineligible students. We furthermore find no evidence that grant holders take longer to complete their degrees than their peers enrolled in comparable programmes. Thus, while access to grants does shift students' college major choices, it does not seem to nudge students with particularly overoptimistic beliefs into demanding majors.[5]

For the rest of the paper, we proceed by first introducing the institutional setting of the Chilean higher education system and the data we use to study the effect of financing schemes on students' choices in Section 2. Our empirical analysis is then split into two parts: a reduced form regression-discontinuity analysis in section 3 and the study of mechanisms through the lens of a choice model in section 4. In section 5, we track students throughout their university career and demonstrate that marginal students entering more challenging subjects because of access to grants are not negatively selected. Finally, section 6 offers a discussion and some concluding remarks.

2 Institutional Setting and Data

In this section, we outline how we can make use of the higher education system of Chile to replicate as closely as possible exogenous variation in the access to two types of financing schemes: student loans and grants. We then move on to describe our data sources and the sample restrictions we impose.

[5]Such subjective beliefs are central to a series of recent studies trying to understand major choices when beliefs about economic returns and one's academic ability are biased (for an overview, see Patnaik *et al.*, 2021). Note that this literature focuses on comparisons of (perceived) returns of majors. Relatively less is known about the sensitivity of major choices to cost shocks when relative gross returns are unaffected (Altonji *et al.*, 2016) – as is the case in our setting of policy-induced changes in the price of all majors.

2.1 Institutional Setting

Until recent years, the higher education system of Chile was characterised by relatively high tuition fees compared to other OECD countries.[6] For our study sample, students at the tenth percentile of the tuition fee distribution pay a yearly fee of approximately 1 million Chilean pesos (CLP; ≈$1,890), whereas the average student pays 2.1 million CLP (see Figure A1 for an overview of the tuition distribution). For comparison, the yearly median household income over the same period is roughly 4.2 million. Only a few students can consequently afford to fully cover the costs of their studies on their own, and the majority require external financing.

The Chilean government provides assistance to students both in the form of direct grants and by backing loans. Both types of financing cover up to a maximum of 90% of a set reference tuition, and access to either is granted using a combination of merit- and need-based arguments. Students are not allowed to combine grants and loans to cover more than this amount. The need component is ensured by restricting eligibility to students from families below a strict household income level, while the merit component consists of a minimum achievement in a standardised nationwide test called *Prueba de Selección Universitaria (PSU)*. Conditional on being eligible in terms of income, a single test score threshold determines whether a given student can receive funding either in the form of a loan or in the form of a grant. Other than allowing students to access grants, neither income nor PSU test scores further determines the level of funding that students can receive.

The PSU test is administered by a department of the University of Chile called DEMRE *(Departamento de Evaluación, Medición y Registro Educacional)* and is offered once a year in December in nationwide local testing centers. It is a classic multiple-choice test that requires students to take two mandatory components – mathematics and language – and at least one of two voluntary components – science and/or history, social science, and geography. For each component, the raw results are standardised at the national level to result in a distribution of scores ranging from 150 to 850, with a mean of 500 and a standard deviation of 110. The relevant test score influencing allocations of financial aid is an equally weighted average of the two mandatory components only.

The combination of household income and PSU test results necessary to obtain a grant is not constant over time since access to grants has been extended between 2011 and 2015. Table 1 summarises this extension by showing the test score thresholds on a yearly basis for several family income bins. While only the bottom 40% of the income distribution was eligible for grants

[6] From 2016 onward, the Chilean government enacted a needs-based system of tuition-free public universities that increasingly covers also private institutions. We focus our attention on the years up to and including 2015.

Table 1: PSU Threshold for Grant Eligibility

Family Income	$2008-2011^{*}$	*2012*	*2013*	*2014*	*2015*
Quintile 1	550	550	500	500	500
Quintile 2	550	550	525	525	500
Quintile 3	N.E.	550	550	550	500
Quintile 4					
Pct. 60 to 70	N.E.	N.E.	N.E.	N.E.	500
Pct. 70 to 80	N.E.	N.E.	N.E.	N.E.	N.E
Quintile 5	N.E.	N.E.	N.E.	N.E.	N.E.

Note: Displayed are the minimum test score averages of math and language that give eligibility to grants, by year and family income quintile. N.E.: not eligible. The thresholds are identical for two types of grants, the Bicentennial grant and the JGM grant, which are received conditional on enrolling in CRUCH and accredited universities, respectively.
$*$ JGM was introduced in 2012.

before 2012, this number rose to 70% in 2015. A similar extension happened with respect to the necessary PSU requirement. A student in the bottom income quintile in 2012 had to obtain at least a math-language average of 550 points, whereas a score of 500 would have been sufficient for the same student in 2015.

Note that there are two separate grants sharing the eligibility thresholds displayed in Table 1. They are related to the two different institution types into which the Chilean higher education system is broadly divided. The first group consists of the so-called traditional or *CRUCH* universities, which are typically considered to be of higher prestige.[7] Conditional on meeting the income and PSU requirements, students enrolled at a CRUCH university are eligible for the *Beca Bicentenario* or Bicentennial Grant (BG), covering up to 90% of a reference tuition that is set by the Ministry of Education based on an assessment of a programme's value-added. As the reference tuition corresponds to 84% of actual tuition on average (Solís, 2024), the BG covers around 76% of tuition fees. The second group of higher education providers includes all other private universities and vocational institutions. Eligible students enrolled at the latter schools are financed through the *Beca Juan Gómez Millas* (JGM), which covers up to 1.15 million CLP (≈$2000) of yearly tuition. On average, this subsidised 75% of tuition costs in JGM programmes, but coverage varies across programmes (see Figure A2 for the distribution of coverage by institution type).

Irrespective of the institution type, any student who is marginally ineligible for a grant in terms of their test score is still eligible for a subsidised student loan: loan eligibility is ensured at

[7]CRUCH is short for Consejo de Rectores de Universidades Chilenas or Council of Rectors of Chilean Universities. Universities in this network can be both public and private.

a PSU cut-off of 475. This implies that students close to the PSU threshold have access to either type of financing for any accredited institution in Chile. It also implies that close to the respective thresholds, assignment to either type of financing is essentially random – a feature that is crucial for our identification strategy outlined in the following section. As is the case for grants, the type of loan is institution-specific, where the loan obtainable when enrolled at a CRUCH university traditionally had more favourable conditions. This so-called FSCU (*Fondo Solidario de Crédito Universitario*) has a fixed interest rate of 2%, and repayment starts 24 months after graduation, with a maximum repayment period of 15 years. The FSCU is income-contingent in that maximum payments are capped at 5% of income. Loans at non-CRUCH institutions are called CAE (*Crédito con Aval del Estado*), are closer to market interest rates, and repayment starts 18 months after graduation, with a maximum repayment period of 20 years. As of 2012, the Chilean government started subsidising the CAE, making it more comparable to the FSCU both in terms of interest rates (now 2%) and income-contingent repayments (cap at 10% of income). When contrasting grants and loans in the Chilean context, it is consequently important to bear in mind that loans already provide some insurance through their income-contingent nature.[8]

While grants and loans are institution-specific, they differ little between majors. That is, conditional on studying at a given university, an economics major and an engineering major are eligible for similar amounts of funding. This is in line with the pricing behaviour of Chilean universities more generally. Most of the variation in tuition we observe in the data is between institutions. Within any given university or vocational school, different fields of study are priced rather homogeneously.[9] In Section 3.5, we provide further information on the set of majors offered by universities and vocational institutions and discuss the role of such supply-side characteristics for our empirical analysis.

In line with most countries, students in Chile apply and are admitted immediately into a given institution-major combination and do not choose their field of study after enrolling. They do

[8]Even though loans are income-contingent, it is not uncommon among Chilean borrowers to default on student loans or delay repayment. According to a report by the Ministry of Education (MINEDUC, 2022), around 25 to 28% of graduates in the years 2012 to 2014 missed at least one out of their last three CAE payments. While this provides a second layer of implicit insurance against the repayment burden of loans, it is important to note that until 2020, any borrower delaying payments or defaulting on loans was automatically listed by credit bureaus, leading to a partial exclusion from the credit market. FSCU loan administrators were additionally authorised to pursue legal action in cases of non-repayment, including the option to withhold salary payments. The burden of default on student loan borrowers is thus substantial.

[9]The R^2 obtained when regressing tuition fees on institution fixed effects in our data is 0.74, which changes to 0.77 if we additionally include fixed effects for the nine aggregate fields of study (STEM, Humanities, ...) that we consider in our analysis below. On the other hand, when regressing tuition fees on only field-of-study fixed effects, we get $R^2 = 0.08$.

so after having received their PSU test result and are thus fully aware of which type of funding they will be able to access. Switching to a different major in later years after enrolment requires a new application, which can rely on old PSU test results. A transfer of financial aid to another institution or another major within the same institution is possible at a maximum of once, and only in justified cases.

2.2 Data and Sample Construction

Through DEMRE (2015), we have access to the universe of Chilean PSU test takers for the academic years 2008 through 2015. Besides detailed information on the disaggregated test results of each individual, the data contains unique identifiers that allow us to merge prospective students with administrative records of the Chilean Ministry of Education (MINEDUC, 2025). This way, we can obtain rich socio-demographic information on family background, gender, and academic performance in high school, as well as enrolment decisions at the institution-major level. We are furthermore able to track the application and assignment of financial aid for each individual in our sample.

To study the effect of various financing types on student choices, we impose the following sample restrictions: (i) students apply for financial aid, (ii) students pre-qualify for grants in terms of the necessary family income quintile requirements outlined in Table 1, (iii) students are first-time PSU test takers, taking the test in the year of their high school graduation, (iv) students apply for financial aid after 2011. Requirements (i) and (ii) ensure that each individual in our sample is at least theoretically eligible for both types of financing. Conditional on applying for aid and fulfilling the income requirement, it will allow us to focus our attention on those applicants who are close to the grant eligibility cut-off in terms of their PSU test scores. Requirement (iii), on the other hand, excludes repeated test takers. Since our identification strategy will rely on a regression-discontinuity design and students are allowed to use their highest obtained test result across different attempts, repeated test-taking would violate the central assumption of a non-manipulable test score. Requirement (iv) helps us to focus our analysis on a population better suited to answer our question of interest. As highlighted in Table 1, the JGM grant was only introduced in 2012. This implies that up to 2012, students passing the grant eligibility cut-off experienced a change in their financial aid status *only if* they enrolled in a CRUCH institution since the BG grant is applicable only there. Given their more prestigious nature, these institutions are generally more difficult to access, and the variation in aid around the cut-off is consequently limited.[10]

A final necessary requirement for our analysis is (v) the exclusion of all individuals for whom the relevant test score threshold for grant eligibility is 500. This excludes all individuals in the year 2015 and the lowest income quintile in the years 2013 and 2014. As we detail in Appendix C, a large subset of Chilean universities partially base their admission decisions on obtaining a minimum PSU result of 500 - the mean of the standardised test score distribution.[11] This leads to a situation in which passing the threshold of 500 not only opens the possibility of obtaining a grant but also significantly enlarges the choice sets in terms of university programmes that are available to prospective students. In other words, for the excluded subjects, two treatments discontinuously change at the cut-off of 500, which we would not be able to disentangle. Importantly, such a change of choice set is not present at any other threshold (see Appendix C).

Imposing the restrictions (i) to (v) leaves us with a sample of 195,031 test takers, out of which 73% end up enrolling in a higher education institution in the year of test taking.[12] Table 2 provides an overview of the socio-demographic composition of our study sample. Roughly three-quarters come from the central regions of Chile, and a third have at least one parent with a higher education degree. A slight majority of 55% is female, and approximately one out of four is enrolled in a science, technology, engineering, or mathematics (STEM) field.

3 Reduced Form Analysis: Grants vs. Loans and Enrolment Choices

3.1 Empirical Strategy and Identification

Given the nature of grant assignment in Chile, a straightforward way to proceed empirically is to estimate regression-discontinuity (RD) models, treating the PSU test result as a running variable. Let $c_{i,q,t}$ be the relevant PSU cut-off for grant eligibility for an individual i with family income in quintile q, applying in year t (see Table 1). Pooling over all the years in our sample described above, we define $PSU_i^* = PSU_i - c_{i,q,t}$ as a normalised running variable and our targeted estimand as the

[10] For completeness, we present all results for the full study period from 2008 onward in the Appendix (Table B1). As expected, they are muted and less precisely estimated yet remain qualitatively unchanged.

[11] Most of the minimum requirements around a PSU score of 500 were introduced as part of a reform raising minimum recruitment standards in teaching/education programmes. See Neilson *et al.* (2022) and De Falco *et al.* (2024) for details.

[12] Among the remaining 27% of test takers, we see that 18% re-take the test in the following year. The remainder either do not enrol in higher education or enrol in subsequent years with their original test result.

standard sharp RD parameter:

$$\tau = \lim_{z \to 0^+} \mathbb{E}[Y_i | PSU_i^* = z] - \lim_{z \to 0^-} \mathbb{E}[Y_i | PSU_i^* = z]. \quad (1)$$

Here Y_i can be either an indicator for enrolment in higher education or in a specific field, respectively (see below), and τ captures the change in the average enrolment decisions for those becoming eligible for a grant. As discussed above, any student marginally below the cut-off has access to a student loan. Our empirical strategy consequently allows us to contrast two types of higher education financing.[13,14]

In practice, we estimate (1) non-parametrically using a kernel-weighted linear regression of the form:

$$Y_i = \beta_0 + \beta_1 \mathbb{1}\{PSU_i^* \geq 0\} + \beta_2 \mathbb{1}\{PSU_i^* \geq 0\} \times PSU_i^* + \beta_3 PSU_i^* + \mathbf{X_i'}\delta + \epsilon_i. \quad (2)$$

The parameter of interest then is β_1, which quantifies potential discontinuous jumps around the normalised cut-offs. We construct weights to estimate (2) following a triangular kernel-weighting around the cut-off within an optimally set bandwidth according to Calonico *et al.* (2020).

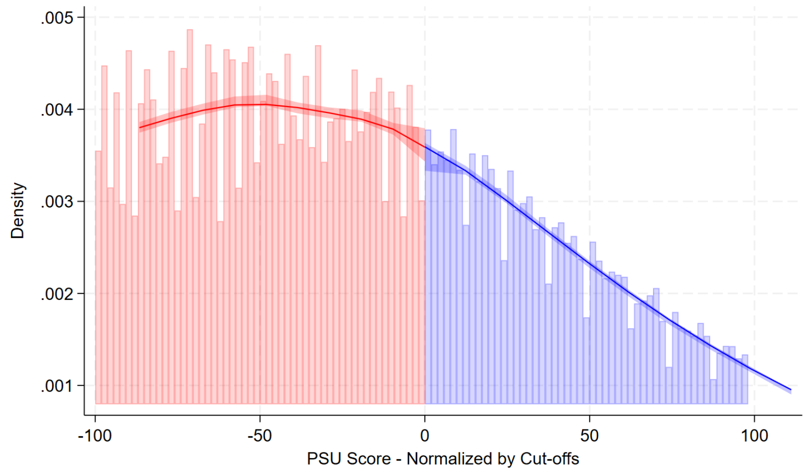
To gain precision in our estimation, $\mathbf{X_i}$ adjusts for a vector of covariates that include the individual's gender and high school GPA, an indicator equal to one in case the student chose to take the voluntary science component of the PSU test, parental education, the number of other studying and working family members, an indicator for single mother households, an indicator for the type of high school, as well as location (far north, near north, central, near south, far south) and year by family income quintile fixed effects.

Identifying Assumptions. Before moving on to the empirical results, we want to briefly discuss the plausibility of the conditions under which β_1 identifies a causal effect. As is standard, the necessary identifying assumption for sharp RD models requires continuity in potential outcomes

[13] We focus on the effect of grant eligibility instead of take-up since the take-up of any type of financing is conditional upon enrolment. Therefore, by definition, any individual taking a grant will be enrolled in higher education.

[14] Since access to loans is only certain with a PSU test score of at least 475 (75 points below the grant cut-off for most of the students in our sample and 50 for some, see Table 1), some students who are far below the cut-off might not have access to student loans. While one could be worried that we include individuals without any access to financial aid in the group of loan takers, most specifications that we estimate use an optimal bandwidth close to or even well below 50 and weight observations using a triangular kernel. This implies that such students are either excluded or receive little weight in the estimation. Our results are robust to restricting the analysis to the subgroup of students for whom the grant eligibility cut-off is at 550 PSU points and thus sufficiently far from 475 such that individuals close to the loan cut-off are not included.

Figure 1: McCrary Test for Discontinuity in Running Variable



Note: The Figure presents a histogram of PSU_i^*, together with confidence bands obtained from the local polynomial density estimator proposed by Cattaneo *et al.* (2020, 2021a).

around the threshold. We might expect a violation of the continuity assumption if students were able to manipulate their PSU score around the cut-off. Bear in mind, however, that the final PSU test result determining grant eligibility is the product of a blind evaluation procedure and a nationwide standardisation of raw test scores that ensures an approximately truncated normal distribution of results. It is, therefore, unlikely that there is a local correlation of the threshold with any observed or non-observed factor that is non-ignorable in terms of our analysis.

In line with this, Table 2 also includes estimates of model (2) treating standard socio-demographic covariates as outcome variables. We find our sample balanced among all but three covariates, which lends additional credibility to our identifying assumption. In every estimation below, we include each of the displayed covariates. A second check for manipulation around the threshold is based on McCrary's (2008) idea of testing for discontinuities in the density of the running variable around the cut-off. Figure 1 plots the histogram of our running variable, PSU_i^*, together with confidence bands based on a local polynomial density estimator proposed by Cattaneo *et al.* (2020, 2021a). We find no evidence for discontinuities in the density of test scores around the cut-off.

As discussed in Section 2.2, our sampling procedure excludes combinations of income quintiles and years in which threshold crossing is also associated with changing choice sets for students. Besides ruling out the presence of a second treatment around the grant eligibility cut-off, this additionally allows us to alleviate concerns about violations of the so-called *Stable Unit*

Table 2: Summary Statistics and Covariate Balance around Grant Eligibility Cut-off

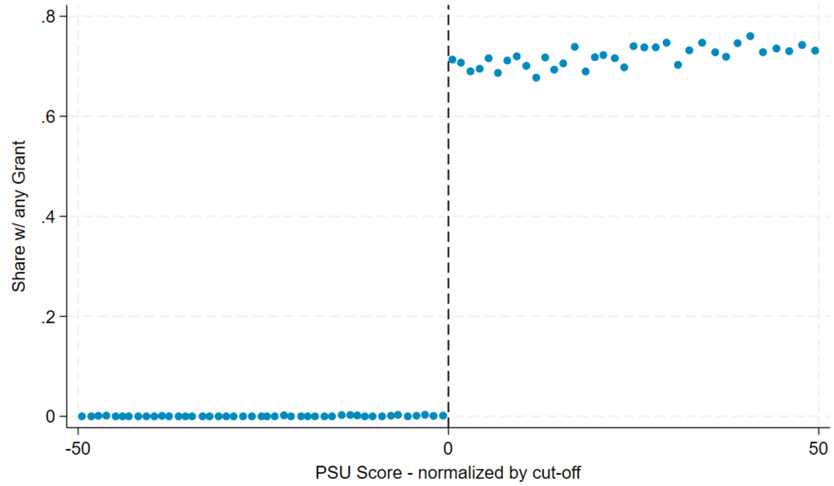
	Sample Mean	Mean at Cut-off (β_0)	RD Estimate (β_1)	Standard Error ($\hat{\beta}_1$)
High School GPA	5.630	5.725	0.003	0.008
# Working Family Members	1.178	1.159	-0.001	0.011
# Studying Family Members	0.101	0.100	-0.004	0.005
Female	0.555	0.540	0.004	0.007
Single Mother HH	0.192	0.188	-0.004	0.004
Academic Parents	0.374	0.445	-0.015*	0.009
Took Science Test	0.597	0.667	0.002	0.009
Municipal School	0.346	0.271	-0.007*	0.004
Subsidise School	0.589	0.673	-0.010**	0.004
Academic School	0.714	0.809	-0.006	0.006
Income quintile $\times$ year:				
Quintile 1 $\times$ 2012	0.232	0.175	0.004	0.015
Quintile 2 $\times$ 2012	0.123	0.118	-0.007	0.010
Quintile 3 $\times$ 2012	0.083	0.091	0.001	0.008
Quintile 2 $\times$ 2013	0.166	0.178	-0.002	0.019
Quintile 3 $\times$ 2013	0.116	0.127	-0.010	0.012
Quintile 2 $\times$ 2014	0.164	0.184	0.006	0.023
Quintile 3 $\times$ 2014	0.117	0.126	0.007	0.013
Region:				
Far North	0.050	0.051	0.000	0.004
Near North	0.062	0.065	-0.002	0.004
Central	0.750	0.740	0.002	0.008
Near South	0.121	0.127	-0.001	0.005
Far South	0.013	0.013	-0.000	0.002

Note: Far north includes the administrative regions of Antofagasta, Arica y Parinacota, and Tarapaca; near north includes Atacama and Coquimbo; central includes Valparaiso, Libertador General Bernardo O'Higgins, Maule, Biobio, and the capital city of Santiago; near south includes Araucania, Los Lagos, and Los Rios; far south includes Aysen, and the Magallanes and Chilean Antarctica. Academic Parents is an indicator equal to one if at least one parent has a higher education degree. Took Science Test is an indicator equal to one in case the student chose science as the voluntary component in the PSU test. Columns 3 and 4 present estimates for β_0 and β_1 in model (2), treating the respective socio-demographic variables as outcomes. Column 5 displays the standard errors for $\hat{\beta}_1$ clustered at the PSU test score level. $^{**}p < 0.05$, $^{*}p < 0.10$.

Treatment Value Assumption (SUTVA). In our context, one might be worried that marginally eligible students cluster in specific programmes and crowd out the enrolment of marginally ineligible peers. If this were the case, however, we would expect a discontinuity in the number of available programmes in students' choice sets at the grant eligibility cut-off. However, we show in Appendix C that the dimensionality of choice sets develops smoothly along the distribution of the running variable.

Taken together, the evidence presented in this section implies that our main identifying

Figure 2: Take-up of any grant around cut-off



Note: The Figure presents shares of individuals holding either the Bicentennial (BG) or the JGM grant in 80 PSU bins around the grant eligibility cut-off (normalised to zero across years and income quintiles). Grant take-up is not at 100% right of the cut-off since grant take-up is conditional on enrolment, whereas we plot the unconditional probability of taking a grant.

assumption is plausibly satisfied, and β_1 identifies the causal effect of crossing the grant eligibility cut-off. The setting we study consequently allows us to focus our analysis on local exogenous variation in access to two different schemes of higher education financing. In line with this, Figure 2 shows that there is, in fact, a discontinuous increase in grant take-up for marginally eligible students. The demand for student loans correspondingly collapses at the cut-off (see Figure A3).[15]

Outcomes and Population of Interest. Our outcomes of interest are binary enrolment indicators. While we consider the extensive margin of enrolment in higher education and enrolment by institution type, the main focus is on enrolment in one of the ten aggregate fields of study as categorized by the Chilean Ministry of Education: Agriculture, the Humanities, the Social Sciences, Business and Management, Arts and Architecture, Education, Law, Health, Technology and Engineering, and the Natural Sciences. We mostly combine the latter two groups into one category, which we define as STEM. Majors in STEM are an interesting group to consider since, as we show below, they are not only characterised by high monetary returns but also by a higher earnings variance and a lower probability of degree completion. For each binary indicator, the reference group consists of

[15] Figure A4 displays the change in take-up at the cut-off separately for the two types of grants. In both cases, demand increases discontinuously at the cut-off, but take-up for the BG is increasing when moving further to the right of the threshold, while it is decreasing for the JGM. This is driven by the fact that the BG grant is applicable only to CRUCH universities, for which higher PSU test scores are required for admission. We cannot plot the take-up of the two types of loans separately since CAE loans are not managed by the Ministry of Education, and we do not have individual-level data for their take-up. Figure A3 thus plots only the take-up of the FSCU loan.

the remaining college majors or non-enrolment. If not explicitly mentioned otherwise, we treat all Chilean higher education institutions identically in the sense that when measuring college major choices, we do not discriminate between students enrolled in a public or private university or in a vocational institution.[16]

When thinking about the external validity of our regression discontinuity exercise, note that our approach to identification is local in nature and relies on the continuity of potential outcomes at the eligibility cut-off. To nonetheless get a feeling of how selected our population of interest is, we can compare the observable socio-demographic characteristics of our full study sample (Table 2, column 2) to that of students at the grant eligibility cut-off (column 3). In terms of gender, region of origin, and family structures, students just below the cut-off closely resemble the average population of financial aid applicants. At the same time, they are more likely to have college-educated parents and to have attended subsidised schools and schools with an academic track. They also scored higher on the PSU test (sample mean 489), suggesting a slightly higher college preparedness. While our population of interest – students at the grant eligibility cut-off – is not a perfectly random sample of applicants for financial aid, the two groups reveal interesting similarities in observable characteristics.

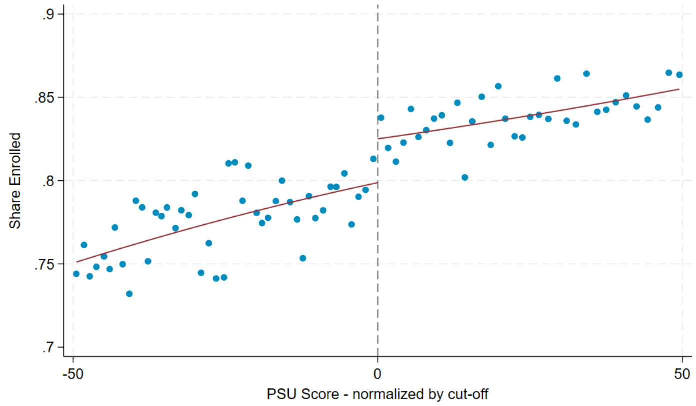
3.2 RD on the Extensive Margin: General Enrolment and Institution Choice

The focus of our analysis is the link between financial aid and college major choices. A prerequisite for choosing a college major, however, is to decide to pursue a higher education degree in the first place. We thereby start by asking the related question of whether grants generally incentivise enrolment in higher education programmes. Previous work by Solís (2017, 2024), focusing on earlier cohorts of Chilean high school graduates, finds evidence that while access to student loans increases enrolment by 18 percentage points, a replacement of loans with grants does not significantly increase enrolment further. Figure 3 plots the share of people enrolled in any higher education programme for different bins of the PSU test score distribution around the grant eligibility cut-off.

Contrary to previous evidence, for our period of study, grant eligibility does encourage some high school graduates to enrol in a higher education programme. General enrolment changes by approximately 3.3 percentage points (Table 3). While this effect is modest both relative to the

[16] Vocational institutions in Chile include so-called Professional Institutes and Technical Formation Centres. Both offer undergraduate degrees focused on a more technical, labour-market-oriented training that typically lasts 2 to 3 years.

Figure 3: General enrolment around the cut-off



Note: The Figure shows shares of students enrolled in any higher education institution in 80 PSU bins around the grant eligibility cut-off (normalised to zero across years and income quintiles).

enrolment rate of marginally ineligible students ($\approx$ 80%) and when compared to the additional enrolment resulting from reduced borrowing constraints (access to student loans), which are the focus of Solís (2017), it is estimated with high precision and statistically different from zero. There are some noteworthy contextual differences between the earlier cohorts studied by Solís and our sample, which could explain why income effects appear to be stronger in the period we focus on. Both general enrolment and tuition fees trended upward over time, resulting in heightened political and public attention dedicated to the financing of higher education. As discussed in Section 2, access to grants was, up until 2012, furthermore heavily restricted based on income and programme types. This implies that only a small share of the population of applicants to financial aid experienced actual changes in their financial aid status around the grant eligibility cut-off.

Besides general enrolment, a second interesting non-major-choice margin to consider is enrolment rates by institution type. Table 3 further presents point estimates of specifications, in which the outcome variable is a binary indicator for enrolment in either CRUCH universities, other private universities, or vocational higher education institutions. The results show that students who are marginally eligible for grants are particularly likely to enrol in more prestigious institutions that are part of the CRUCH network (as opposed to vocational higher education institutions or non-traditional private universities). These institutions are generally considered to be of higher quality, implying significant gains in expected monetary returns (Hastings *et al.*, 2013). Note that, even though the estimates for general enrolment and enrolment in CRUCH are of similar size, it does not need to be the case that all (or even most) students choosing to enrol in higher education because of grants necessarily sort into CRUCH institutions. Instead, the effect likely also reflects

Table 3: Effect of Grants vs. Loans on Enrolment in Different Institution Types

	enrolled in:			
	Any Institution	CRUCH	Private Uni	Vocational
RD_Estimate	0.033***	0.033***	0.008	-0.006
	(0.008)	(0.010)	(0.008)	(0.007)
Effective N	41,675	41,675	52,522	44,191
Mean at cut-off	0.797	0.357	0.295	0.146
Bandwidth	32	32	41	34

Note: *** $p < 0.01$.
All dependent variables are binary indicators. Reference category: non-enrolment or enrolment in other types of institutions. The Table presents estimates for β_1 in equation (2). All specifications are estimated using local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors, clustered at the PSU test score level, are displayed in parentheses. Effective N summarises the number of observations within the chosen bandwidth. Mean at cut-off refers to the enrolment for marginally ineligible students (below the cut-off).

switches from students who, without access to a grant, would otherwise have enrolled in a different institution type. We will revisit this point on marginal enrollees versus switchers in further detail below when interpreting our results on college major choices.

3.3 RD on College Major Choice

As just documented, the type of financial aid that students receive to finance their studies has implications for the type of higher education institution they choose to enrol in. In this section, we present evidence that, beyond this, financial aid is also not neutral in terms of college major choices. Focusing first on the average effect of grant eligibility on enrolment in STEM majors, we present point estimates in Table 4.

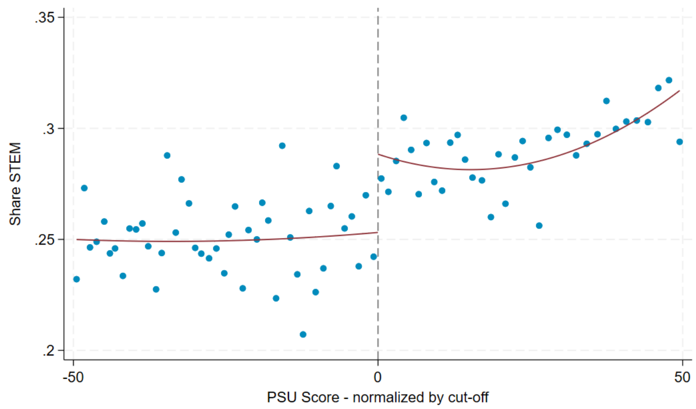
As indicated by column (1), those prospective students who do marginally qualify for a grant are 2.9 percentage points more likely to enrol in STEM-related fields than those who would have to rely exclusively on student loans to finance their education. To put this into perspective, note that the enrolment rate in STEM fields for marginally ineligible students is approximately 25%. The RD estimate thus points towards an increase in enrolment of approximately 11.5%. Columns (2) and (3) of Table 4 further differentiate STEM fields into engineering-related majors and the natural sciences. It highlights that the mass of changes we observe for the aggregated STEM category can be traced back to engineering degrees. However, the baseline level of enrolment in the natural sciences is significantly lower, with only 2.1% of those marginally ineligible for grants enrolling in

Table 4: Effect of Grants vs. Loans on Enrolment in STEM

	(1) STEM	(2) Engineering	(3) Science
RD_Estimate	0.029***	0.024***	0.005*
	(0.008)	(0.007)	(0.003)
Effective N	52,004	55,560	62,118
Mean at cut-off	0.253	0.232	0.021
Bandwidth	41	44	49

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
All dependent variables are binary indicators. Reference category for STEM, Engineering, and Sciences: non-enrolment or enrolment in any other major. The Table presents estimates for β_1 in equation (2). All specifications are estimated using local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors, clustered at the PSU test score level, are displayed in parentheses. Effective N summarises the number of observations within the chosen bandwidth. Mean at cut-off refers to the enrolment for marginally ineligible students (below the cut-off).

Figure 4: Enrolment in STEM fields around the cut-off

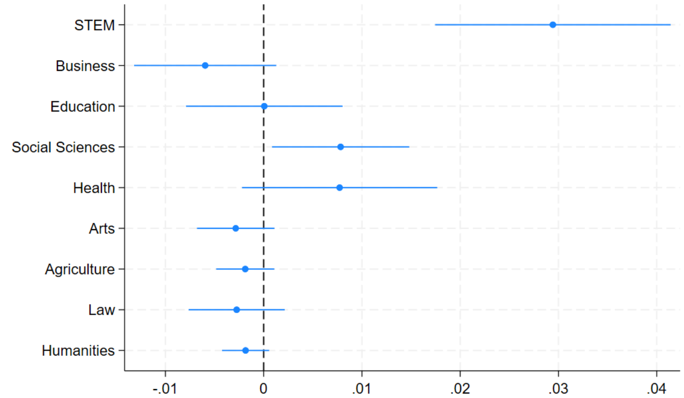


Note: The Figure shows shares of students enrolled in STEM fields for 80 PSU bins around the grant eligibility cut-off (normalised to zero across years and income quintiles).

science programmes, but 23.2% enrolling in engineering. Relative to these baseline numbers, the observed change is considerably larger in the natural sciences.

The finding that STEM enrolment rates increase in response to grant eligibility is robust to different bandwidth choices and functional forms. Figure 4 provides non-parametric evidence for this by plotting mean enrolment rates in STEM fields for students in separate bins of PSU test score points around the cut-off. While enrolment rates are quite volatile for those ineligible for grants, there is hardly any group of students above the threshold with enrolment rates below 26%. Correspondingly, the results are stable when repeating the estimation across vastly different

Figure 5: Effect of Grants vs. Loans: all Fields



Note: The Figure presents estimates and confidence intervals for β_1 in specification (2), using the respective variables as outcomes. Reference categories for the fields of study: non-enrolment or enrolment in any other field. Each specification includes the covariates outlined in Table 2. For exact values, see Table B2.

bandwidths, ranging as far as from 20 to 80 PSU points (see Figure A5).[17] When splitting the sample along the lines of gender, parental education, or parental income, we find positive enrolment rates in STEM fields for every considered subgroup.[18] In a final robustness check, we repeat the same RD specification on a sample of students who are ineligible for grants: those who took the PSU test in order to apply for universities but are excluded from financial aid access because their family income is too high (i.e., quintiles four and five of the distribution, see Table 1). This placebo exercise reveals no effect on the ineligible population (see Figure A6), increasing our confidence that our empirical approach picks up a genuine treatment effect and no other spurious changes at the eligibility cut-off.

Moving beyond STEM degrees, we note that the results for the remaining eight aggregate fields of study are less precisely estimated. Figure 5 displays point estimates and confidence intervals using each of the fields separately as an outcome. We observe a slightly higher enrolment in the social sciences and health fields and a slightly lower enrolment in the humanities and arts. Enrolment in the social sciences increases by 0.8 percentage points. When interpreting the magnitude of the estimated effects, there are two things to bear in mind. First, enrolment rates for marginally ineligible students differ widely across fields. The estimated effect on enrolment in

[17]The fact that results are robust to a bandwidth choice as narrow as 25 points is particularly re-assuring since it excludes observations with PSU scores around 500, which, as discussed in Section 2.2, is a problematic value given the admission policies in Chile.

[18]There is only limited evidence for heterogeneity in the response to financial aid when considering the 9 aggregate major classifications. We do find some evidence that men respond to grant eligibility by increasing enrolment in engineering, whereas women are more likely to sort into the natural sciences. Appendix D discusses heterogeneity in greater detail, considering, besides socio-demographics, also heterogeneity across different grant eligibility cut-offs.

social sciences, for instance, corresponds to a 12% increase relative to the mean marginally below the cut-off, which is comparable to the effect we find for STEM enrolment.[19]

Second, the reference category for our outcome variables contains both enrolment in other fields and non-enrolment. In combination with the previously documented positive effect of grants on general enrolment, this implies that there is a mechanically positive relationship between grant eligibility and the enrolment rate in any field. The fact that we see negative point estimates on five out of nine fields of study is only feasible because students switch their college majors in response to becoming eligible for grants. To provide more intuition for this, Table B3 contains the following hypothetical scenario: if all students choosing to enrol in higher education because of grants (3.3%) were to select programmes in the same proportion as their peers marginally below the cut-off, what would the resulting increase in enrolment rates by field look like? In this scenario, the resulting point estimates would mechanically be positive for each field of study and equal to 1.1% in the case of STEM. This is in contrast to our actual estimates for STEM (2.9%), highlighting that grant eligibility encourages students to pick STEM fields at considerably higher frequency. At the same time, the gap between the mechanically positive effect we should expect on enrolment rates in the humanities (0.04%) and what we actually observe (-0.2%) corresponds to almost 25% of the overall enrolment in the humanities for students marginally below the cut-off (1%).[20]

Interestingly, Hastings *et al.* (2013) estimate STEM, health, and social science degrees to be those with the highest monetary returns in Chile, whereas the humanities are characterised by lower returns. A first glance at our data could consequently suggest that we see a positive effect of grant eligibility on the likelihood of enrolling in higher return fields and a negative effect on enrolment in lower return fields. This is at odds with findings for US universities (Rothstein and Rouse, 2011; Stater, 2011; Sjoquist and Winters, 2015a,b; Andrews and Stange, 2019; Hampole, 2024) and Germany (Boelmann *et al.*, 2024), where the opposite seems to be the case. At the same time, we do observe negative (albeit insignificant) point estimates on enrolment in law and business degrees - two categories of college majors that do not qualify as low-return fields. To better characterise the average programme choices of students at the cut-off, the next section moves beyond a description of changes in the chosen fields of study and instead uses a categorisation based on the programme's characteristics as outcomes in the RD framework.

[19]Figure A7 re-scales the point estimates in Figure 5 to account for these baseline differences and illustrates that the effect sizes on enrolment in STEM, the Social Sciences, and the Humanities are comparable.

[20]Figure A8 shows the point estimates for each field of study, conditional on enrolment in higher education. Also this analysis reveals increased enrolment in STEM, at the expense of enrolment in arts, law, and the humanities.

3.4 Characterisation of Chosen Programmes

In 2011 the Chilean Ministry of Education started a transparency initiative that included, among other goals, an attempt to improve the programme choices of prospective university students. Using information derived from past university graduates matched to administrative tax return data, they accumulated programme-specific information on a set of labour market indicators and other programme characteristics. Since then, prospective students can retrieve programme-specific information for aggregated combinations of major and institution types on an easy-to-access and easy-to-navigate homepage (www.mifuturo.cl). In this section, we use the data from this *MiFuturo* initiative to characterise the choices of students in our sample.

Data: Mifuturo. *MiFuturo* contains data on combinations of majors and institution types, such as, for example, environmental chemistry at a university or social work at a vocational institution. Going forward, we will refer to such major by institution-type combinations simply as programmes. The information used to characterise programmes stems from the universe of students entering the Chilean higher education system from 2000 onward and includes: labour market earnings in the first five years after graduation – both the average level and selected percentiles of the distribution – employment rates within 2 years of graduation, the formal time to graduation (according to study regulations) and the average actually realised study duration, the share of female students, the share of students from subsidised and public schools, respectively, and the share of students passing their first year of study.[21] Data on this is summarised in the so-called *buscador estadísticas por carrera* (search engine for career statistics, MIFUTURO, 2013b) and displayed transparently for interested prospective students. [22]

We are able to match about 89.3% of our sample directly to information from MiFuturo, based on institution type and the name of the majors students are enrolled in. For an additional share of slightly over 5% of our sample, we can impute the programme information based on near matches. For instance, if we do not have access to information about programme characteristics of a specific major in one type of vocational institution – e.g., *Instituto Profesional* – but we do have information on the same major in the second vocational institution type – in this case, *Centro de Formación Técnica* – then we use the respective information for imputation.[23] The resulting sample

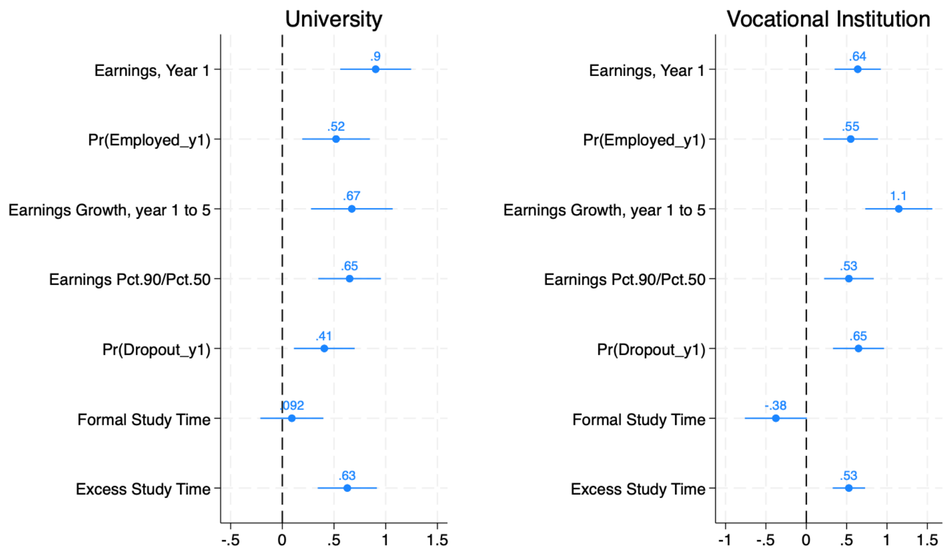
[21] Earnings are computed conditional on employment and drawn from administrative tax records.

[22] See Figures A9 and A10 for an example involving the average earnings trajectories, formal and realised time to graduation, and gender composition of mathematics and statistics at universities.

[23] Appendix E provides greater details about the imputation procedure.

contains 135,029 students enrolled in 246 narrowly defined programmes.

Figure 6: STEM/No-STEM Differences in Programme Characteristics



Note: The Figure uses data from *MiFuturo* at the programme-level. Each row displays point estimates and 95% confidence intervals for β_1 from regressions of the type $X_i = \beta_0 + \beta_1 STEM_i + u_i$, where X_i are the respective displayed programme characteristics. Programme characteristics are standardised to a mean of zero and a standard deviation of one. The left column uses only programmes offered at universities, whereas the right column uses programmes in vocational institutions. Programmes are weighted by the number of enrollees.

There is a large degree of variation across programmes in almost every available dimension. For instance, in the programme with the lowest dropout rates, only 7% of students do not continue after one year of study; this number rises up to 54.7% in some programmes (see Table B4 for summary statistics across the 246 alternative programmes). Similarly, average earnings one year after graduation range from 226,800 CLP monthly in the lowest-earning programme to 2.3 million in the highest. STEM programmes make up a substantial share of all included alternatives (22% of university programmes and 33% of vocational programmes). Figure 6 presents differences between STEM and non-STEM programmes for a selection of labour market and study-related indicators. In line with what we would expect, STEM degrees are indeed those with, on average, higher earnings. In contrast to evidence from the US (Andrews *et al.*, 2022), they also have a considerably higher variability of earnings as measured by the ratio of the 90th earnings percentile to median earnings. At the same time, dropout rates in STEM majors at universities are around 4 percentage points higher than in other fields, which corresponds to almost half a standard deviation of dropout rates across programmes, and students are more likely to require a longer time than formally stated to finish STEM degrees.

RD Results: Characterising Chosen Programmes. As a first step toward understanding the driving forces behind the effect of financial aid on major choices, we characterise the programmes selected by marginally eligible students, compared to those chosen by loan takers, along two dimensions: labour market returns and risk, where risk encompasses both academic uncertainty and earnings volatility. We focus on measures that are directly observable by students on the official website (earnings one and five years after graduation, employment rates, and dropout rates), as well variables that we construct but that are directly inferable from information provided by *MiFuturo*: (i) earnings growth between the first and fifth year after graduation, (ii) earnings variability, defined as the ratio of the 90th percentile of earnings to median earnings five years after graduation, and (iii) excess study time, which we define as the difference between the formal and average realised time until degree completion.[24]

Column 1 of Table 5 shows that, on average, the characteristics of programmes chosen by students on both sides of the cut-off look similar, and differences are estimated imprecisely.[25] While the point estimates suggest that students with access to grants can expect to outearn their peers with loans by approximately one monthly salary ($\approx$ 690,000 CLP) over the first five years after graduation, this difference is small relative to the 30% higher earnings associated with STEM degrees at universities. However, it is important to bear in mind that even though our results indicate that financial aid affects college major choices of students, switchers are still the minority at the cut-off. A more informative exercise in line with the discrete nature of the RDD so far is to create taxonomies of programmes and estimate the share of switchers across programme categories at the cut-off. We do so by classifying programmes based on terciles of the cross-programme distribution of each characteristic.

The last three columns of Table 5 present estimates from RD regressions, where the outcome variables are mutually exclusive dummies equal to one if a student is enrolled in a programme associated with low, medium, or high values of the respective characteristics. Students who are marginally eligible for grants are 2.2 percentage points more likely to enrol in fields associated with high earnings five years after graduation. Given that average earnings in this category are 1.6 million CLP, this amounts to a significant switch in expected earnings relative to enrolling in

[24]*MiFuturo* provides additional information on the socio-demographic composition of programmes; see Table B4 for an overview. We include this richer set of characteristics in the discrete choice model in Section 4.

[25]See Figures A11 and A12 for a non-parametric representation.

Table 5: Grants vs. Loans: Differences in Programme Characteristics

	Avg. Differences	Enrolled in:		
		Low	Medium	High
	(1)	(2)	(3)	(4)
Earnings, year 1	0.082	-0.014	0.011	0.003
	(0.061)	(0.009)	(0.009)	(0.011)
Earnings, year 5	0.139	-0.017*	-0.005	0.022**
	(0.100)	(0.010)	(0.010)	(0.009)
Earnings Growth, year 1 to 5	0.005	-0.010	-0.008	0.019*
	(0.004)	(0.010)	(0.012)	(0.011)
Earnings Ratio 90/50, year 1	-0.001	0.003	-0.009	0.006
	(0.005)	(0.008)	(0.007)	(0.008)
Pr(Employed_y1)	0.005*	-0.032***	0.026***	0.006
	(0.003)	(0.011)	(0.010)	(0.010)
Pr(Dropout_y1)	-0.003	0.007	0.009	-0.016
	(0.002)	(0.012)	(0.012)	(0.012)
Excess Study Time	0.044	-0.019*	0.008	0.011
	(0.034)	(0.011)	(0.011)	(0.009)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The Table presents estimates for β_1 in equation (2). Column (1) estimates average differences in the characteristics of programmes chosen by grant recipients and loan takers, whereas for each specification in columns (2) through (4), the outcome variables are indicators for enrolment in a field associated with low, medium, and high values of the respective characteristics as measured by terciles 1, 2, and 3 of the distribution of characteristics across the set of programmes in which individuals within 25 PSU points around the grant eligibility cut-off enrol. Each model is estimated using weighted local linear regressions and includes the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020).

low and medium-return programmes, where average earnings are, respectively, 0.6 million and 0.9 million CLP. At the same time, grant eligibility increases enrolment in fields with high, i.e., steep, earnings growth profiles over the first five years of their careers by 1.9 percentage points. This is in line with findings by Hampole (2024), who shows that students in the U.S. are willing to trade off lower earnings immediately after graduation for steeper earnings growth. However, contrary to her results, we do not find evidence that students with grants select programmes with lower initial earnings, suggesting that intertemporal trade-offs are less relevant in our setting. We also do not find evidence that grant recipients select programmes with higher earnings variance.

Splitting the categorisation of programmes into terciles reveals some interesting non-linearities of transitions. Students appear to switch from programmes with relatively low earnings to programmes with relatively high earnings. In contrast, the switch in earnings trajectories is from lower categories to high-growth programmes. Similarly, students with grants are significantly less likely to enrol in programmes with (i) a low share of students exceeding the formally required study duration and (ii) a low probability of employment shortly after graduation. While in the latter case, the probability mass shifts towards programmes with average employment probabilities, the shift is spread out across both higher categories when considering excess study time. These non-linearities are indicative of a richer underlying structure of switching where transitions are unlikely to be driven by one characteristic in isolation. Programmes can be categorised by a rich set of characteristics, and if they are correlated, the observed changes we are presenting in this section can only be a first step.

Thinking about the evidence presented in Table 5 in this light can also help to understand the counterintuitive result that students at the cut-off are more likely to enrol in STEM fields, which are characterised by higher than average dropout rates, but are not more likely to enrol in fields with high dropout rates. As presented in section 3.2, students also adjust their institutional choices when grants become available. They are more likely to enrol in (CRUCH) universities than in vocational higher education institutions. Given the overall higher quality at universities, dropout rates are 12 percentage points below those at vocational institutions, potentially offsetting the higher dropout rates in STEM. Nonetheless, dropout rates vary significantly also within the more aggregated categories displayed in Table 5. To understand their role in informing students' choices and the impact of financial aid, we need to keep institutional and other characteristics fixed when comparing dropout rates across programmes. We view the presented evidence as motivation to do so through the lens of a discrete choice model, which we present below.[26]

3.5 Discussion of RD Evidence

Before moving to the discrete choice model, we want to use this Section to recap the evidence coming from the RD analysis and to discuss potential issues in its interpretation. We demonstrate that students with access to grants are more likely to enrol in higher education, particularly at CRUCH universities. They are also more likely to sort into STEM fields and, more generally, fields

[26]Figures A13 through A16 provide further evidence of the correlation between programme characteristics by highlighting several pairwise comparisons. Earnings uncertainty after graduation and degree completion uncertainty are positively correlated at the programme level, as are earnings after graduation and excessive study times. Dropout rates are positively correlated with initial earnings in vocational institutions but negatively correlated in universities, where natural sciences account for a larger share of STEM degrees than in vocational institutions.

with higher earnings potential and steeper earnings growth trajectories.

The observation that grant eligibility jointly affects general enrolment, enrolment in CRUCH universities, and college major choices introduces two difficulties for thinking about the identification of the interaction between financial aid and programme characteristics. First, if universities happened to be more specialised in STEM-related fields, we might misinterpret a desire for enrolment in more prestigious institutions as the choice of STEM. Relatedly, we could ask whether students with grants are really more likely to choose programmes because of their steeper earnings growth or if university programmes are characterised by both steeper earnings trajectories for their graduates and other not-considered characteristics affecting students' choices. We think about this set of issues broadly as supply-side considerations.

Second, is the increase in STEM enrolment driven by students switching between different majors or by marginal students who, without grants, would not have enrolled in higher education but do enrol in STEM if offered a grant? Note that from a policy point of view that is interested in understanding the effect of replacing grants with student loans, the RD analysis delivers causal estimates of what we should expect the resulting distribution of college majors to look like for students around the grant eligibility cut-off in Chile. For this, a distinction between whether the effects are driven by marginal enrollees is not needed, given that the regression-discontinuity assumptions are plausibly satisfied. The same is true for unobserved supply-side considerations. However, both questions are highly relevant for our understanding of the mechanisms underlying the observed changes and, therefore, for the generalisability of our findings to other contexts.[27] We can alleviate part of the concerns directly within the estimation of the discrete choice model, as we show below. Before going there, however, we want to present some more reduced-form evidence.

Supply Side Considerations. There are several reasons why we think an alternative supply-driven explanation is unlikely to explain the observed increased enrolment in STEM. At the more aggregated level, universities and vocational institutions appear similar in terms of their field-level specialisation. While 31.2% of all offered degrees at universities can be classified as STEM, the respective number is 31.7% for vocational institutions (see Table B5). The picture changes somewhat if we focus on CRUCH universities separately from other universities. For them, 40.7% of all degrees are STEM-related, according to our classification. However, the higher share of STEM

[27]Even within the higher education system of Chile, we could think about generalisations of the effect away from the cut-off. Given the limited variation in cut-off values, however, there is only limited information to use. We touch upon this issue briefly in Appendix D when discussing heterogeneity by cut-off.

fields at CRUCH universities relative to vocational institutions is driven exclusively by the natural sciences, for which we see highly significant but small (0.5 percentage point) increases among students with access to grants. This is not sufficient to explain the aggregate impact on enrolment in STEM (2.9 percentage points).

Naturally, STEM fields at CRUCH institutions might be different from STEM fields at other institutions, making them particularly attractive. In this case, a simple comparison of shares of offered degrees across institution types might not be sufficient. For this to explain the increase in STEM enrolment at the cut-off, it is not sufficient that universities overall have more attractive features than vocational institutions; it would have to be differentially so for STEM degrees. While we do not have access to proxies for the attractiveness of different fields within the same exact institution, *MiFuturo* offers a second data set called *buscador de instituciones* (search engine for institutions, MIFUTURO, 2013a) that contains information on a series of quality indicators at the institution level. We use this to ask whether, within an institution type, those institutions that are more focused on STEM degrees are observably different from those institutions with a lower focus on STEM degrees; a proxy for the relative attractiveness of aggregate fields within institution types. To do so, we divide institutions based on the share of students enrolled in STEM and label those with above median shares as STEM-intensive and those with below median shares as non-intensive.

Within CRUCH universities, STEM-intensive and non-intensive universities are similar with respect to a large set of quality indicators, including the share of professors with a Ph.D. or a Master's degree, the overall number of professors, and the stock of computers with internet access that is available for students' use (see Table B6). At STEM-intensive institutions, the ratio of students to professors is slightly higher than at non-intensive institutions (27.3 vs. 21.14), indicating that, if anything, STEM-intensive institutions have slightly less desirable characteristics. More generally, the variation in our considered set of quality indicators is considerably larger across institution types (private universities vs. CRUCH) than across institutions with a different field composition within institution types. We argue this makes it less likely that our results on STEM enrolment simply pick up a desire to enrol in more prestigious, high-quality programmes.

In a final set of tests, we repeat our RD analysis with two modifications. First, we interact the STEM enrolment indicator with indicators for enrolment in specific institution types (CRUCH, private universities, vocational) and use the corresponding categories as outcomes. The results indicate that while the point estimate on enrolment in STEM fields at CRUCH universities is the largest, it corresponds only to two-thirds of the overall effect we find on STEM (see Table B7). Not all STEM enrolment is consequently absorbed by CRUCH institutions. A second test repeats the RD analysis using a STEM enrolment indicator as an outcome, but conditions on institution fixed effects. We provide suggestive evidence that enrolment in STEM might increase at the cut-off, also *within* institutions (see Table B8). Clearly, this latter result should be interpreted with caution, given that institution and major choices are taken contemporaneously and are both affected by financial aid.

Marginal Enrollees vs. Major Switchers. Given the unobservability of counterfactuals, it is not feasible (without strong assumptions) to perfectly distinguish the group of students that only enrolled because of grant eligibility (*marginal enrollees*) from the ones that would have enrolled regardless (*potential major switchers*). To reiterate a point made above, this is unproblematic for answering the question of how grant eligibility affects enrolment in STEM and other fields. It could be either group driving the result, and our RD analysis picks up a weighted average, which is identified. However, if marginal enrollees are a selected group, then their trade-offs between varying programme characteristics might differ from the trade-offs considered by major switchers, since our discrete choice model below will condition on enrolment. Our conclusions about how financial aid affects the relative evaluation of each choice feature might thus be affected. Ruling out selection at the extensive margin is consequently intimately linked to the identifying assumption of our choice model.

While we do not have a separate instrument shifting only the extensive margin of enrolment, we can provide suggestive evidence that marginal enrollees are not selected based on observable characteristics. In Table B9, we demonstrate that there are no statistically significant group differences in the response to changes in financial aid at the extensive margin along the lines of family income and parental education. The same is true for the case of gender: women are 3.3 percentage points more likely to enrol in higher education if grants become available, while for men, enrolment increases by 3 percentage points. Given the stark differences in STEM enrolment rates across genders, this is reassuring in that it is a first proxy against an extensive margin response of individuals with potentially high idiosyncratic preferences for STEM fields. Instead, we find positive and significant enrolment effects for all considered subgroups.[28] Considering the full set of available individual characteristics, we show in Table B10 that, also conditional on enrolment, the sample is balanced at the grant eligibility cut-off.

[28] The fact that we do not find a null effect on general enrolment in any subgroup prevents us from using such a hypothetical group to study major switching when general enrolment is constant.

4 Mechanisms: The Role of Different Programme Characteristics

The RD analysis presented above reveals that, on average, access to grants increases enrolment rates in STEM degrees and higher return fields more generally. While STEM degrees are also associated with higher dropout rates, students at the cut-off are not generally more likely to choose fields with high dropout rates, suggesting the presence of several (potentially counteracting) trade-offs made by students. In this section, we shed light on the mechanisms driving our reduced form results and try to disentangle different channels through which financial aid affects individual college major choices.

To do so, we estimate a discrete choice model for a sub-sample of individuals close to the grant eligibility cut-off and predict their enrolment in narrowly defined programmes using a host of observable programme characteristics. We are particularly interested in the question of how the valuation of characteristics, such as average earnings, dropout rates, etc., differs if we consider students marginally above and below the eligibility cut-off. This is informative of how financial aid alleviates or aggravates students' concerns about each respective programme characteristic, holding constant all other included observable programme-level information.

4.1 The Discrete Choice Model

As highlighted throughout the paper, there are many (potentially complex and dynamic) ways in which financial aid and its payback structure might interact with individual college major choices. For the purpose of contrasting the role of the substantial set of programme characteristics outlined above, the model that we present in this section deliberately reduces complexity and models a static college major choice problem of students with and without access to grants. We think of it as a reduced-form way of capturing key trade-offs between, for instance, initial earnings and their trajectories.[29]

Consider two types of students that differ in their financial aid status $g \in \{Grant, Loan\}$. They face a single choice among $j = 1, 2, ..., J$ alternative programmes, defined in line with the *MiFuturo* data as a combination of institution type (university, vocational) and major. Each programme

[29] In line with the reduced form model interpretation, we explicitly allow preferences to be treatment-dependent. This implies that we are not attempting to estimate "deep" parameters as is standard in much of the discrete choice literature. We are contrasting two groups with significantly different outlooks on their post-university debt levels. Our exercise on differences in the valuation of study-related uncertainty, for instance, is then closer in spirit to estimating levels of absolute risk aversion for groups with different wealth levels than to estimating common parameters of relative risk aversion.

is characterised by a set of K characteristics, denoted by $x_{j,k}$.

Let the utility individual i derives from choice j be:

$$U_{ij}^{g} = \sum_{k} x_{j,k}(\tau_k^g + \beta_k^g PSU_i^*) + \epsilon_{ij}, \tag{3}$$

where PSU_i^* is individual i's PSU test score, normalised by the relevant grant eligibility cut-off, and ϵ_{ij} is an idiosyncratic programme-specific taste shock.

We allow for an interaction between each characteristic $x_{j,k}$ and PSU_i^*, which has two key advantages. First, by normalising PSU_i using the grant eligibility cut-off, τ_k^g is informative for the utility contribution of programme-characteristic k for members of group g at the cut-off (i.e., for $PSU_i^* = 0$). This naturally merges the discrete choice approach with the logic of the regression-discontinuity design, in that $\Delta_k = \tau_k^{Grant} - \tau_k^{Loan}$ quantifies the discontinuity in the valuation of k at the cut-off. Importantly, τ_k^g is to be understood as the ceteris paribus effect of a characteristic k, disentangling its impact from that of other characteristics $\_k$. Second, the PSU test result partially affects admission chances and, thereby, the choice sets of students. While there is no discontinuity in the choice sets of students at the cut-off (see discussion in Section 2 and Appendix C), interacting programme characteristics with individual PSU test results away from the cut-off captures differences in the valuation of x_{jk} that are possibly driven by access to a larger set of programmes with a different make-up in terms of observable characteristics, and not by financial aid.

As is standard in discrete choice modelling, we assume that ϵ_{ij} is i.i.d. type I extreme value, which, together with the utility specification (3), implies that the probability of individual i choosing any programme j has the classic conditional logit form:

$$Pr_i(j) = \frac{exp(\sum_k x_{j,k}(\tau_k^g + \beta_k^g PSU_i^*))}{\sum_{s=1}^{J} exp(\sum_k x_{s,k}(\tau_k^g + \beta_k^g PSU_i^*))}. \tag{4}$$

We use this theoretical probability together with the programme information retrieved from *MiFuturo* and the choices made by individuals in our regression-discontinuity sample to estimate the parameters $\{\tau_k^g, \beta_k^g\}_k$ by maximum-likelihood. Similar to our analysis in Section 3.3, we restrict our estimation to individuals within a narrow bandwidth around the grant eligibility cut-off and estimate the model locally using a triangular kernel weighting.

We discuss three potential ways to interpret the model results. First, we present estimates of Δ_k directly. This is informative of changes in the evaluation of programme characteristic k, conditional on other characteristics $\_k$, at the cut-off. While this provides direct evidence on the channels through which financial aid affects college major choices, the magnitude of the logit coefficients is notoriously difficult to interpret. In a second approach, we thus construct ”willingness to pay” measures by financial aid type. A standard way to do so is to consider the ratio of two coefficients, $\frac{\tau_k^g}{\tau_{\_k}^g}$ (Train, 2009). While each coefficient individually is not directly interpretable, their ratio eliminates the arbitrary utility scaling inherent in their estimation and quantifies the respective trade-off. We can, for instance, ask how much earnings growth individuals in either subgroup are willing to give up in order to reduce dropout rates by focusing on $\frac{\tau_{Dropout}^g}{\tau_{Earnings\_Growth}^g}$.

A final common approach to interpreting discrete choice model estimates is to convert the results into marginal effects. The marginal effect of a change in characteristic $x_{j,k}$ on the probability of choosing programme j at the cut-off is:

$$\frac{\partial Pr_i(j|PSU_i^* = 0)}{\partial x_{j,k}} = \tau_k^g \times Pr_i(j|PSU_i^* = 0)\left(1 - Pr_i(j|PSU_i^* = 0)\right). \tag{5}$$

A complication with following this approach is that there are $|J| \times |J| \times |K|$ marginal effects: a marginal effect for each programme and characteristic, including ”own” elasticities and ”cross” elasticities – e.g., there are separate marginal effects for enrolment in programme j if dropout rates in programme j or in programme $\_j$ were to change. To reduce dimensionality, we focus on a subset of programme characteristics and exclusively on ”own” elasticities as displayed in equation (5). For each programme j and included characteristic k, we then calculate the difference in marginal effects between grant and loan takers and report both the average difference and the distribution of differences across programmes.

4.2 Identification

Before turning to the empirical results, we want to highlight some features of the multinomial RD approach that help us with identification as well as challenges.

If we consider estimating the choice model separately by group g, the identifying assumptions for β_k^g and τ_k^g are those of standard conditional logit models. On top of the classic *Independence of Irrelevant Alternatives (IIA)* assumption, we require the assumption that there are no omitted programme characteristics that are (i) correlated with the included set $\{x_{jk}\}_k$ and (ii) non-ignorable for students’ choices of programmes. It is unlikely the case that we can fully characterise students’ choices with our set of included programme characteristics, implying that β_k^g and τ_k^g are unlikely to be identified by our approach.[30]

However, our goal is to study utility *differences* at the cut-off. This implies that even if the levels of valuation for each group (β_k^g, τ_k^g) are not identified, we can recover the difference in evaluations if the omitted variables biasing the estimation of levels are not themselves correlated with the grant eligibility cut-off. That is, we need to rule out that not included programme characteristics are differentially valued by grant recipients and loan takers. In this case, the bias cancels out by considering the difference in coefficients. While this assumption is fundamentally untestable, we are able to adjust for many potential confounders. In particular, we include indicators for the nine aggregate fields of study we considered as outcomes in the RD framework, as well as institution-type fixed effects. All conclusions we draw on the differences in valuations for labour market outcomes and study-related uncertainty are thus based on variation within these macro-categories.[31] We also control for tuition fees as additional proxies of unobserved quality, all labour market and study-related indicators discussed in Section 3.4, and the socio-demographic composition of programmes in terms of gender and high school background (see Table B4 for an overview).

One advantage of focusing on changes at the eligibility cut-off and limiting the sample to individuals in a narrow bandwidth around it is that if the continuity assumptions underlying the regression-discontinuity analysis above are valid, then it is irrelevant that our utility specification (3) abstracts from group-specific tastes. For example, not specifying choice features such as gendered tastes for some programmes is unproblematic if the share of female students is continuous at the cut-off. A similar argument applies to not-specified preference parameters such as patience or risk-aversion, which have been shown to affect college major choices (Patnaik *et al.*, 2022), and to students' admission chances into various programmes. One complication in moving from the RD setting to the estimation of (4) is that we cannot include non-enrolment in higher education in the choice set since there is no obvious counterfactual for some of the important characteristics that we consider in the model (e.g., dropout rates and excess study time). A key identifying assumption of our approach is, therefore, that grant eligibility does not lead to a selection into enrolment for students with unobserved tastes related to labour market returns and uncertainty about degree completion. In the previous section, we demonstrated that even conditional on enrolment, our

[30] Unless, of course, in the unlikely scenario that omitted variables are uncorrelated with x_{jk}.

[31] This also provides further robustness against supply-side considerations discussed in the previous section, as we explicitly allow students' valuation of institution-types to differ by financial aid status.

sample is balanced on a large set of observable characteristics, providing evidence in favour of our identifying assumption.

While we can address some concerns about the validity of our identifying assumption directly, they are certainly more restrictive than the assumptions underlying our RD analysis. We consequently interpret the results below as suggestive rather than conclusive evidence for the proposed channels through which financial aid affects individual college major choices.

Limitations of the MiFuturo Data. There are two shortcomings of the data provided by *MiFuturo*. First, it does not necessarily translate directly into individual-level subjective expectations about programme-specific returns. However, given the easy access to programme-level information it provides for prospective students, we argue that the included information can reasonably be interpreted as an anchor for actual expectations of incoming students.[32] Since our research design relies on a comparison between grant recipients and student loan takers, a stark difference between programme characteristics provided by *MiFuturo* and subjective expectations would moreover be problematic only if expectation errors were correlated with aid status. A second issue with the *MiFuturo* data is that the level of aggregation of programmes is too high to include geographic information at the programme level. We can, therefore, not include city fixed effects, fixed effects for the precise institution an individual enrols in, or the distance between the location of a programme and the home location of an individual.

4.3 Results

Columns (1) and (2) of Table 6 display estimates for the valuation of various programme characteristics by financial aid type. The underlying sample corresponds to the sub-population of students in our RD sample (see section 2.2) within a 20 PSU point window around the grant eligibility cut-off. As before, we estimate the model using triangular kernel weighting and cluster standard errors at the PSU test-score level. In addition to the displayed variables, each model additionally adjusts for 9 aggregate fields of study dummies, institution-type fixed effects, the share of students from subsidised and public schools, the share of female students, the variance in earnings as measured by the ratio of percentiles 90 to 50, and the change in variance over the first five years after graduation.

[32]In line with this assumption, Figure A17 in the Appendix demonstrates that Google search queries for *Mi Futuro* spike in January, the period in which students send out their application packages. Using survey data, Hastings *et al.* (2016) show that Chilean high school graduates have accurate perceptions of college costs but noisy and slightly upward-biased expectations about earnings after graduation.

Finally, each specification contains an indicator for programmes with imputed information and also adjusts for tuition fees.[33]

The results suggest that both groups of students value programme characteristics such as employment probabilities or earnings growth positively and dropout rates negatively. Note that before the estimation, we standardise each programme characteristic, such that the coefficients can be interpreted as the latent utility response to a one standard deviation change in the respective characteristics. Given this, the magnitudes imply that for both financial aid types, a one standard deviation change in dropout rates has a stronger impact than a corresponding change in any other characteristic. Students overall seem to be highly sensitive to this measure of study-related uncertainty. At the same time, students seem to place little value on finishing their degree on time, at least conditional on a large set of programme characteristics. While, as mentioned before, we have less confidence in correctly identifying the levels of valuation than we do in identifying the differences between grant recipients and loan takers, this provides some suggestive evidence that the accumulation of debt through a longer study duration seems to play less of a role than the implied significant costs associated with not finishing a degree at all.

Column (3) contains our coefficient of interest: the difference in valuation between the two financial aid types. Students with access to grants place a higher value on earnings growth after graduation. Other labour market indicators, such as initial earnings and the probability of employment, are not valued differently across the two groups. Hampole (2024) demonstrates that students at U.S. universities who need to finance their studies with loans are less willing to trade off short-term earnings losses for longer-term earnings growth potential. Our model estimates confirm that student loan takers value earnings growth trajectories less than their peers with access to grants. At the same time, we find that, adjusted for a series of correlated programme characteristics, this does not necessarily imply lower initial earnings.

Moving beyond labour market indicators, we do identify study-related uncertainty as a second significant margin of adjustment. The results indicate that replacing student loans with grants leads to considerably less emphasis on programme-level dropout rates when choosing what to study. We also find some evidence that students care less about excessive study times if they are eligible for a grant, even though the group-specific levels are not estimated precisely. The estimated

[33] Note that we use an aggregation of programmes as choice options. We accordingly proxy tuition by the number of programmes within each aggregated option j that fall within one of seven bins of tuition fees, where the smallest bin is below 500,000 pesos, the next bin is 500,000 to 1,000,000, etc. The highest bin contains programmes with tuition fees above 3 million pesos. This information is provided through the website *MiFuturo*.

Table 6: Valuation of Characteristics across Aid Types

	(1) Loans	(2) Grants	(3) $\Delta_k = (2) - (1)$
Excess Study Time	-0.023	0.050	0.072*
	(0.028)	(0.033)	(0.043)
Pr(Dropout_y1)	-0.489***	-0.396***	0.093**
	(0.038)	(0.027)	(0.047)
Earnings, year 1	0.015	-0.026	-0.041
	(0.039)	(0.035)	(0.052)
Earnings Growth, year 1 to 5	0.166***	0.241***	0.075**
	(0.024)	(0.020)	(0.032)
Pr(Employed_y1)	0.137**	0.127**	-0.010
	(0.056)	(0.059)	(0.081)
N Individuals	10,932	10,394	
N programmes	246	246	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Columns (1) and (2) of the Table present estimates for the utility parameters of individuals at the cut-off, τ_k^g, separate by financial aid type. Column (3) instead displays the estimated difference $\Delta_k = \tau_k^{Grants} - \tau_k^{Loans}$. All characteristics were standardised to have a mean of zero and a standard deviation of 1. *Excess Study Time* is the time until graduation of an average graduate minus the formal time to graduation as specified in the study regulations. *Pr(Dropout_y1)* is the share of students dropping out after one year of study. *Pr(Employed_y1)* is the share of graduates in employment one year after graduation. Each model additionally adjusts for the field of study: STEM, Humanities, Health, Law, Arts, Social Sciences, Agriculture, Education, Business and Management, the share of students from public and subsidised schools, the share of female students, tuition fees, institution type (university / vocational), the earnings pct. 90/pct. 50 ratio, the change in the earnings pct. 90/pct 50 ratio between year 1 and year 5, an indicator for enrolment in a field for which characteristics were imputed, and the interaction of each characteristic with individuals' PSU score. Standard errors are clustered at the PSU test-score level and displayed in parentheses.

differences are significantly different from zero across a wide range of bandwidth choices (see Figure A18).

One general issue with interpreting the results of discrete choice models is that the coefficients relate to a latent utility model that scales coefficients with a common arbitrary factor proportional to the variance of unobserved choice characteristics (Train, 2009). As long as this variance is constant across the group of loan takers and grant recipients, we can interpret Δ_k directly as the changing impact of a one standard deviation change of characteristic k on students' choices around the cut-off. Note that the assumption that the variance of unobserved factors is constant is related to our identifying assumption: we need to assume the absence of omitted variables that are correlated with both the grant eligibility cut-off and with our included set of programme characteristics. Even without assuming common variances, however, we can eliminate the scaling

Table 7: Trade-Offs between Programme Characteristics: $\frac{\tau_k^g}{\tau_{k'}^g}$

	$\frac{Dropout}{Employment}$	$\frac{EarningsGrowth}{Employment}$	$\frac{Dropout}{EarningsGrowth}$
Loans	-3.563	1.212	-2.946
Grants	-3.126	1.898	-1.643

Note: The table presents ratios of coefficients by financial aid type, see also Table 6. The programme attributes are standardised, such that the ratios quantify trade-offs between one standard deviation changes. The standard deviation for dropout rates across all programmes is 8.87%, for employment probabilities 13.77%, and for earnings growth 19.33%.

factor by focusing on the ratio of coefficients, i.e., on trade-offs between different programme characteristics.

Table 7 displays the relationship between dropout rates, employment probabilities, and earnings growth separately by financial aid type. Given the standardisation of programme characteristics, the ratios imply that students in both groups are willing to accept programmes with, respectively, 3.1 and 3.6 standard deviations lower employment probabilities to reduce dropout risk by one standard deviation. Put differently, student loan takers are willing to accept a 5.5 percentage points lower employment probability in the year after graduation to reduce dropout risks by 1 percentage point. For grant recipients, the equivalent is 4.9 percentage points. Similarly, students with grants are willing to accept fields with 0.9 percentage points lower employment rates to boost earnings growth by an additional percent, whereas loan takers are willing to accept fields with 1.4 percentage points lower employment rates to reach the same gain in earnings. The trade-off between dropout rates and earnings growth changes most drastically given that students at the cut-off change their evaluations of each characteristic in opposite directions. Students with loans are willing to forgo 6.4% of total earnings growth over the first five years after graduation to avoid programmes with a 1% higher dropout rate. Students with grants are only willing "to pay" 3.6% of future earnings growth.[34]

Grants thus drastically affect students' willingness to take risks and allow them to choose fields that boost their earnings trajectories. To relate this to students' marginal propensity to choose

[34] The dropout to earnings growth ratio is statistically different between the two groups with $p = 0.03$. For the other two comparisons, we do not have sufficient precision to reject the null of equal effects. Using a Taylor approximation, we can construct standard errors for the ratios as $S.E.(\frac{\hat{\tau}_k^g}{\hat{\tau}_{k'}^g}) = (\frac{\hat{\tau}_k^g}{\hat{\tau}_{k'}^g})^2 \times [\frac{Var(\hat{\tau}_k^g)}{(\hat{\tau}_k^g)^2} + \frac{Var(\hat{\tau}_{k'}^g)}{(\hat{\tau}_{k'}^g)^2} - 2\frac{Cov(\hat{\tau}_k^g, \hat{\tau}_{k'}^g)}{\hat{\tau}_k^g \hat{\tau}_{k'}^g}]$. Given that we estimate the model separately by financial aid type, the covariance between the two group-specific ratios is zero, and we can construct the standard error for the difference in ratios as: $\sqrt{S.E.(\frac{\hat{\tau}_k^G}{\hat{\tau}_{k'}^G})^2 + S.E.(\frac{\hat{\tau}_k^L}{\hat{\tau}_{k'}^L})^2}$.

a given programme, we can convert the estimated coefficients from Table 6 into marginal effects. Focusing only on the marginal effects of changes in programmes' own characteristics rather than on cross-programme elasticities, the average marginal effect of dropout rates is -0.16 percentage points for grant holders and -0.2 percentage points for loan takers. Figure A19 plots the distribution of marginal effect differences across all 246 choice alternatives. Note that with 246 included choice alternatives, enrolment in the average programme is 0.4%. A one standard deviation change in dropout rates is consequently associated with a drop in enrolment in that programme by 50%. The difference in marginal effect is 0.04 percentage points, which corresponds to around 10% of total enrolment in the average programme. For the case of excess study time and earnings growth, the differences in marginal effects are 0.03 percentage points on average.[35]

5 Realised Graduation and Time To Completion

The analysis of the mechanisms behind enrolment decisions supports the notion that students financing their education through grants value study-related risks less negatively. However, this is a conditional statement. Unconditionally, we do not find evidence that students with access to grants are more likely to enrol in high-risk degrees on average. In this section, we perform a final exercise in which we track students after enrolment to understand whether we nonetheless see a difference between grant recipients and loan-takers in realised dropouts and time to degree completion. Such differences might arise if students who switch majors because of grant eligibility are negatively selected relative to average enrollees.[36] The latest cohort in our sample started in 2014, allowing us to track students up to eight years after their first enrolment.

Results Table 8 presents regression-discontinuity estimates based on specification (2), in which we compare enrolled students marginally above and below the grant eligibility cut-off in terms of their graduation rates and years to degree completion. In column (1) of Table 8, we show that the

[35]Marginal effects in our choice model include both the estimated evaluation of the characteristic and the probability mass in the considered programme (see equation 5). When contrasting the marginal effects between loan takers and grant recipients, we are consequently not only comparing differences in the valuation of programme characteristics but also differences in the probability of choosing programme *j* at the cut-off. One might be concerned that this change in the probability mass is driven by changes in the valuation of several characteristics, which is precisely what we want to avoid by using the model in the first place. In practice, however, the changes in probability are not substantial enough to meaningfully affect our findings. When fixing the probability mass at the level of marginally ineligible students and constructing the difference in marginal effects purely based on this probability mass and the change in estimated coefficients, the resulting differences are unchanged.

[36]An additional mechanism working against higher dropout rates among grant recipients is that grants can alleviate financial stress and the need to work during students' college years (Broton *et al.*, 2016).

Table 8: Effect of Grants vs. Loans on Graduation Conditional on Enrolment

	Graduated in...		**Years to Completion in...**			
	Any (=1)	STEM (=1)	Any (=1)	Any (=1)	STEM (=1)	STEM (=1)
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	0.008	-0.004	0.071**	0.040	0.152**	0.075
	(0.010)	(0.013)	(0.035)	(0.026)	(0.068)	(0.057)
Mean at Cut-off	0.607	0.464	5.823	5.823	5.623	5.623
Bandwidth	63	79	38	47	62	67
Effective N	62,061	24,961	24,358	29,736	9,503	10,247
# Semester Required			No	Yes	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The table presents estimates for β_1 in equation (2). All specifications are estimated using weighted local linear regressions. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors are clustered at the PSU test score level and reported in parentheses. Effective N summarises the number of observations with non-zero weight given the chosen bandwidth. Mean at Cut-off refers to the graduation probability (columns 1 and 2) and Years to Completion (columns 3 to 6) for marginally ineligible students (below the grant eligibility cut-off). The estimation sample for columns 1 and 2 contains students enrolled in higher education in the year of their first PSU attempt in the respective category, and students graduating within 8 years after enrolment in columns 3 to 6.

change in the probability of graduating once eligible for a grant is precisely estimated close to zero. This is also true when focusing on the population of students enrolled in STEM programmes (see column 2). For our sample, we consequently find no evidence of detrimental effects of financial aid on graduation rates.

In terms of time to degree completion, we find that marginally eligible students spend 0.071 additional years in college. When focusing on the individuals who enrolled in STEM, the effect is slightly larger: approximately 1 out of 7 students who enrolled in STEM and are marginally eligible for a grant spend an additional year in college. While this might be indicative of adverse behavioural responses of students to grant eligibility, note that an alternative explanation is that students with grants might be more likely to enrol in programmes that require more time to be completed also according to their formal study requirements – recall that grant eligibility shifts students from vocational institutions into universities, where degrees are typically longer. In columns (4) and (6) of Table 8, we repeat the analysis, conditional on the number of semesters formally required to finish the respective programme chosen by each student. By doing so, we can assess the influence of eligibility status on student behaviour, independent of programme duration. The coefficients are halved relative to a specification that doesn't adjust for programme length. Collectively, our results suggest a limited role for adverse selection or behavioural responses of grant holders.

6 Concluding Remarks

Using large administrative records from Chile, we find that students who are marginally eligible for grants make vastly different college major choices than students who have to rely on loans. They are more likely to enrol in STEM-related fields and, more generally, in fields with better employment prospects and higher earnings. We, therefore, provide evidence that more generous financial aid does not necessarily imply that students opt for fields with low pecuniary returns – a finding that seems to be the case in a select set of US universities.

With the help of a discrete choice model over heterogeneous higher education programmes, we illustrate different mechanisms underlying these reduced-form results. In particular, we find that, keeping other programme characteristics fixed, grants allow students to worry less about dropout rates and excessive time to degree completion and to enrol instead in high-return programmes. From a methodological point of view, our approach allows us to characterise the interaction between financial aid and specific programme characteristics while holding other programme features constant. Given the correlation between different programme characteristics, this allows us to provide a more comprehensive picture of the mechanism through which financial aid alters students' choices. In fact, unconditionally, students with access to grants are not more likely to enrol in high-risk degrees than loan takers, indicating that programmes with higher dropout rates have competing characteristics viewed favourably by loan takers.

Our analysis relies on local variation around a sharp grant eligibility cut-off. Given the institutional setting in Chile, being marginally eligible corresponds to being among the average students in terms of academic preparedness, since the requirement for eligibility is scoring 525 or 550 points in the standardised PSU test, which ranges from 150 to 850 and has a mean of 500. Contrary to other studies looking at merit-aid targeted towards particularly qualified students (Sjoquist and Winters, 2015b), our results are, therefore, informative for policies targeted at more average students.

When interpreting our results in light of the financial aid environment of other countries, it is important to keep in mind that students in Chile make their enrolment decisions fully aware of their financial aid status and that the aid application and allocation setting is relatively transparent. Previous studies point to uncertainty about eligibility as a strong determinant of financial aid effectiveness (Bettinger *et al.*, 2012; Dynarski *et al.*, 2021). Contrary to other institutional settings, this type of uncertainty is strongly mitigated in Chile. Policy conclusions drawn from the results should take this into account. Nonetheless, our results indicate that financial aid is unlikely to leave the composition of college majors unaffected. While the discussions about optimal financing schemes for higher education are typically focused on the extensive margin of college attendance, we highlight that such policies have (potentially unintended) consequences.

Acknowledgments

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Online Appendices

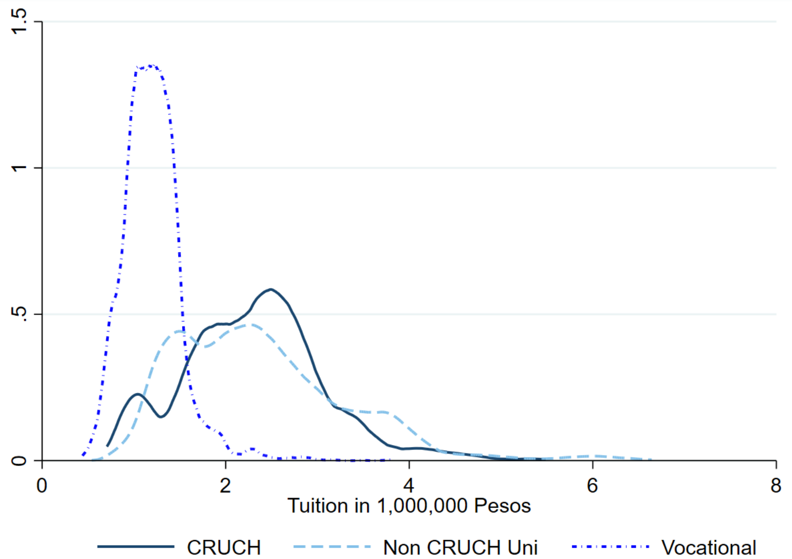
Grants vs. Loans: the Role of Financial Aid in College Major Choice

Adriano De Falco and Yannick Reichlin

July 2025

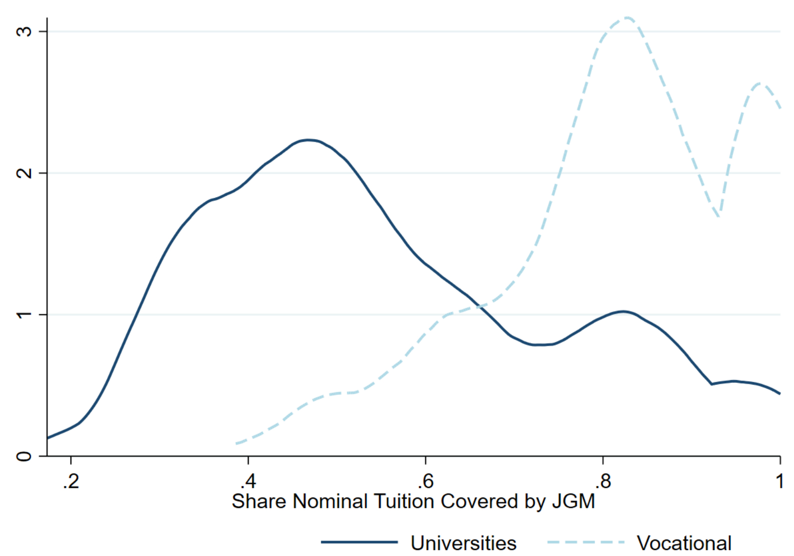
A Additional Figures

Figure A1: Distribution of Tuition Fees by Programmes



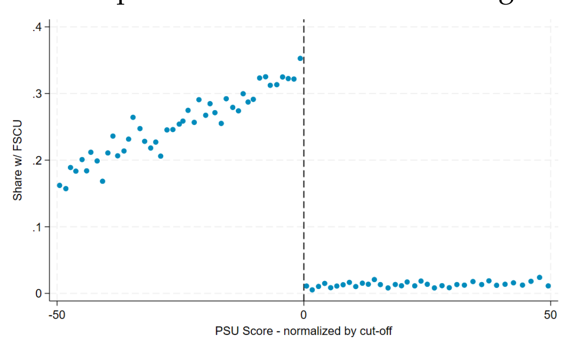
Note: The Figure shows the distribution of tuition fees across programmes, separate for three institution types: CRUCH universities, other non-CRUCH (private) universities, and vocational higher education institutions.

Figure A2: Density Average Coverage JGM



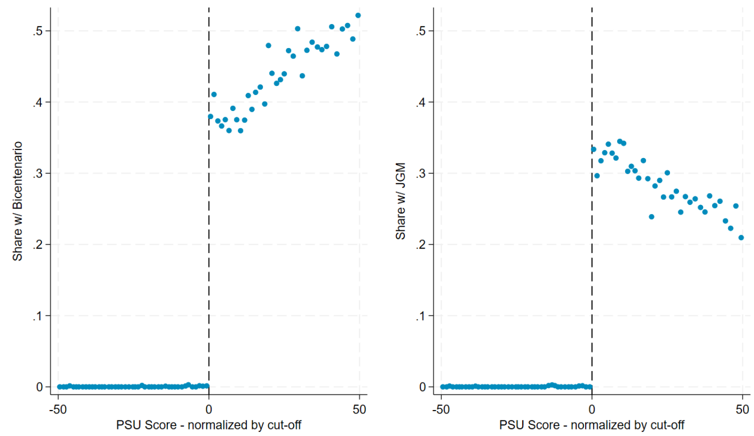
Note: The Figure shows the density of average tuition coverage by the Juan Gómez Millas (JGM) grant across the set of programmes for which we observe at least one student in our data financing their studies with the JGM. The dark blue line refers to university programmes, while the light blue to vocational.

Figure A3: Take-up of FSCU loan around the eligibility cut-off



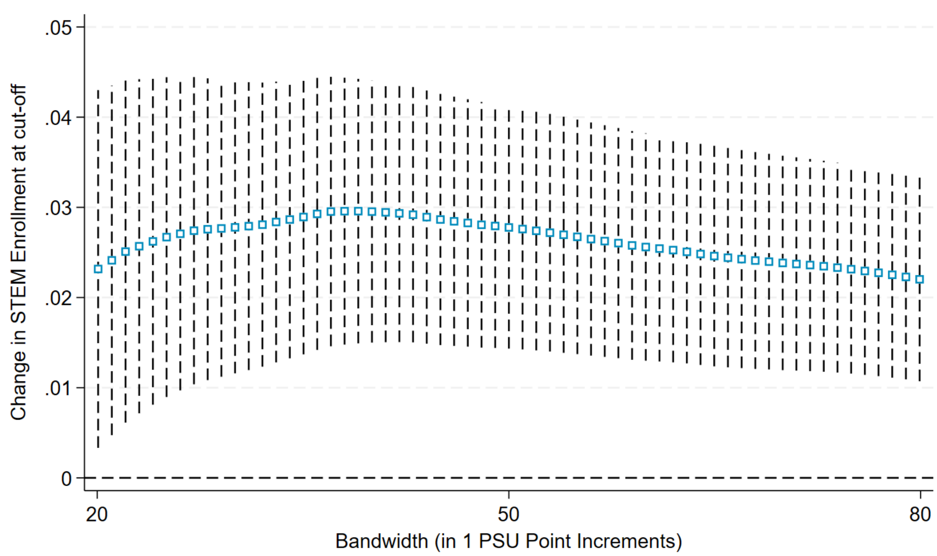
Note: The Figure shows the average take-up of FSCU student loans in 80 PSU bins around the grant eligibility cut-off (normalised to zero across years and income quintiles). FSCU can be used only for enrolment in CRUCH institutions. Take-up is not 100% because we plot unconditional take-up. Conditional on enrolment in a CRUCH institution, take-up is close to 100%.

Figure A4: Take-up of Bicentennial Grant and JGM around the eligibility cut-off



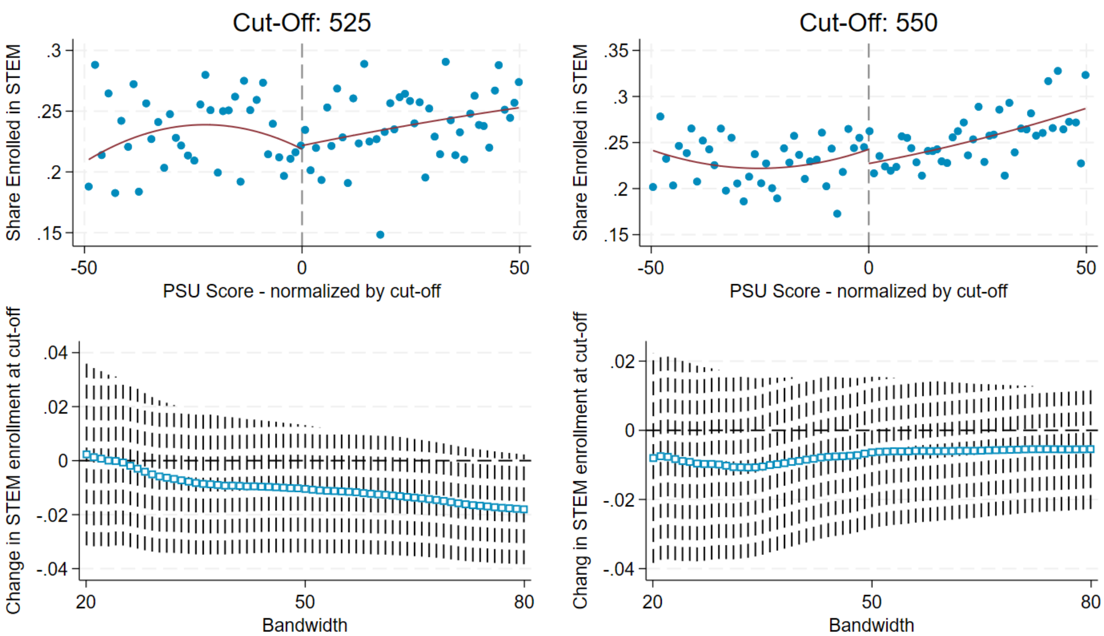
Note: The Figure shows the average take-up of the Bicentennial Grant (left) and the JGM Grant (right) in 80 PSU test score bins around the grant eligibility cut-off (normalised to zero across years and income quintiles). The Bicentennial Grant can be used only for enrolment in CRUCH institutions. The take-up of both grants is not at 100% because we plot unconditional take-up.

Figure A5: Effect of grant eligibility on STEM at the cut-off as a function of bandwidth



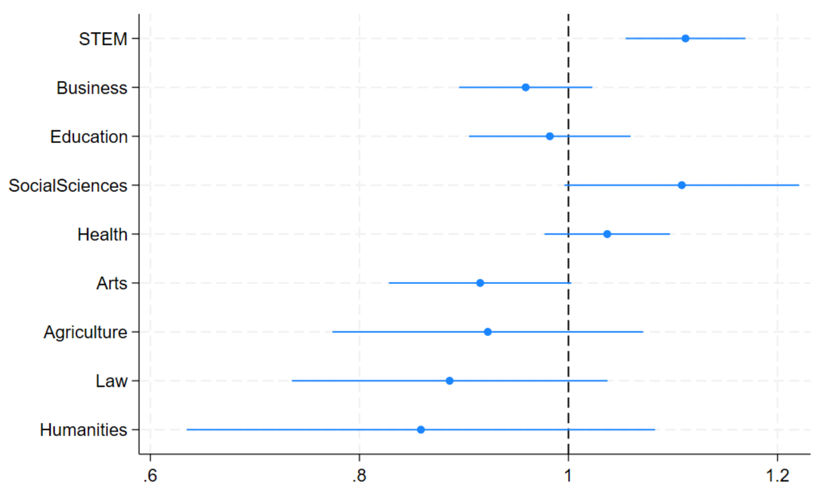
Note: The Figure shows estimates and 95% confidence intervals for β_1 in specification (2) of the main text; for different value of the bandwidth.

Figure A6: Placebo Test for Enrolment in STEM



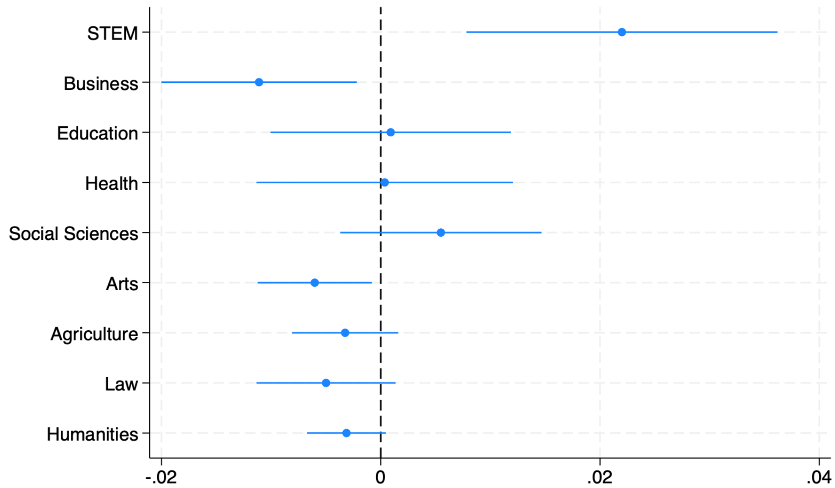
Note: The Figure shows placebo tests for the effect on enrolment in STEM. The estimation sample consists of students who applied for financial aid but are ineligible for grants because their family income is too high (fourth and fifth quintile). The cut-offs were normalised around 550 PSU points in the left-hand-side graphs and around 525 points in the right-hand-side graphs. The upper two graphs display average enrolment rates in STEM fields in 80 PSU test score bins around the cut-offs. The lower two graphs show point estimates and 95% confidence intervals for β_1 in specification (2) of the main text; for different values of the bandwidth in 1 point increments.

Figure A7: Effect of Grants vs. Loans Relative to Baseline Enrolment



Note: The Figure shows the ratio of the shares of marginally eligible students choosing each respective option to the corresponding share of marginally ineligible students. See also Figure 5 in the main text for the point estimates on percentage point changes at the cut-off that are used to construct the ratios here.

Figure A8: Effect of Grants vs. Loans: all Fields - Conditional on Enrolment



Note: The Figure presents estimates and confidence intervals for β_1 in specification (2) of the main text, using the respective variables as outcomes. The analysis conditions on enrolment in any higher education programme - i.e., the reference categories for the fields of study do not include non-enrolment. Each specification includes the covariates outlined in Table 2. The bandwidth is fixed to 50 in every specification.

Figure A9: Screenshot of mifuturo.cl

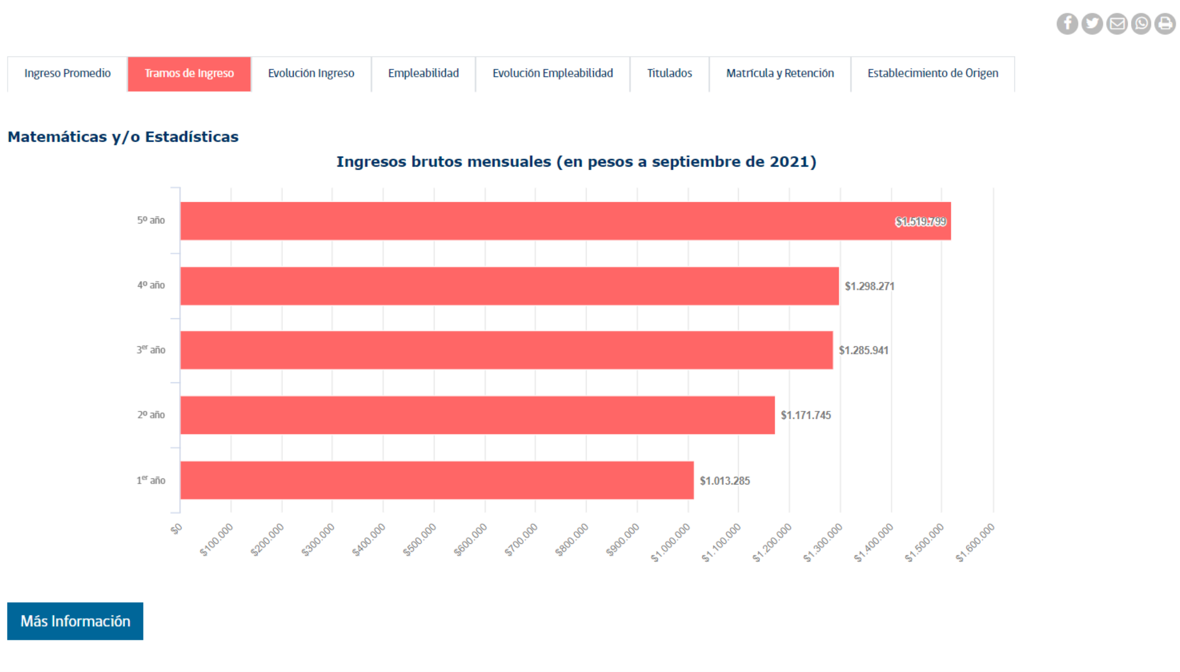
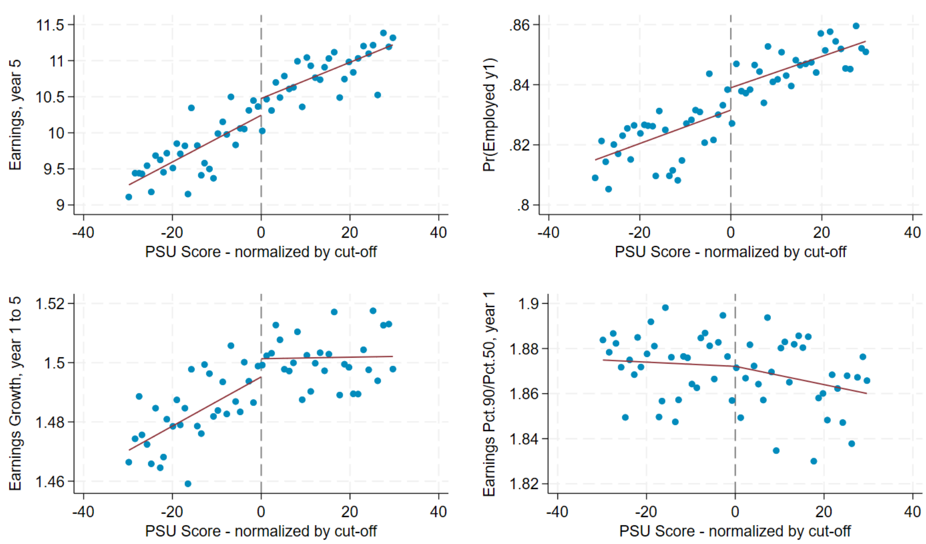


Figure A10: Screenshot of mifuturo.cl

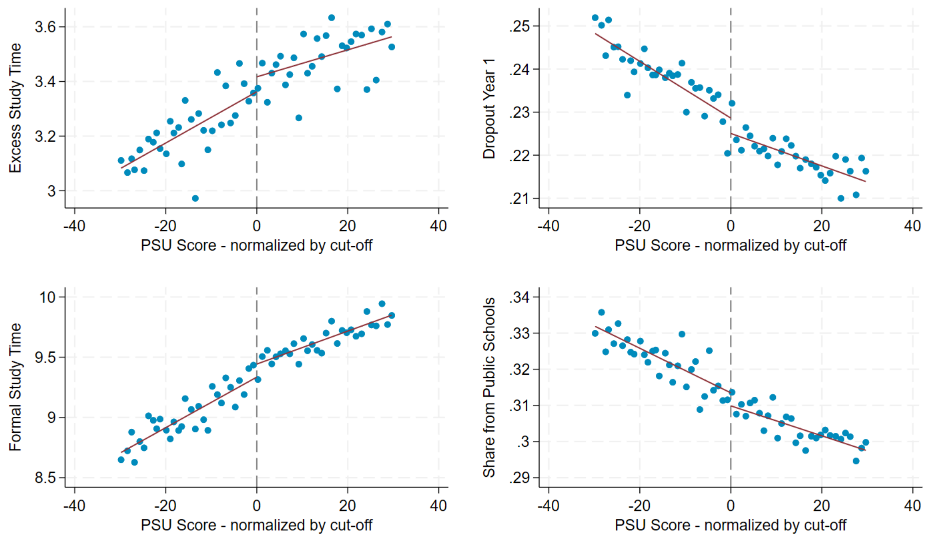
Note: The Figures displays a screenshot of mifuturo.cl and illustrates how interested students can retrieve programme-level characteristics. In this case, the evolution of average wages over the first five years for past graduates of the majors (up), the number of graduates and the number of semesters needed to finish the programme - actual and realised from the previous cohort- (down) for Mathematics and/or Statistics at universities.

Figure A11: Characterisation of Chosen Programme - Labour Market Characteristics



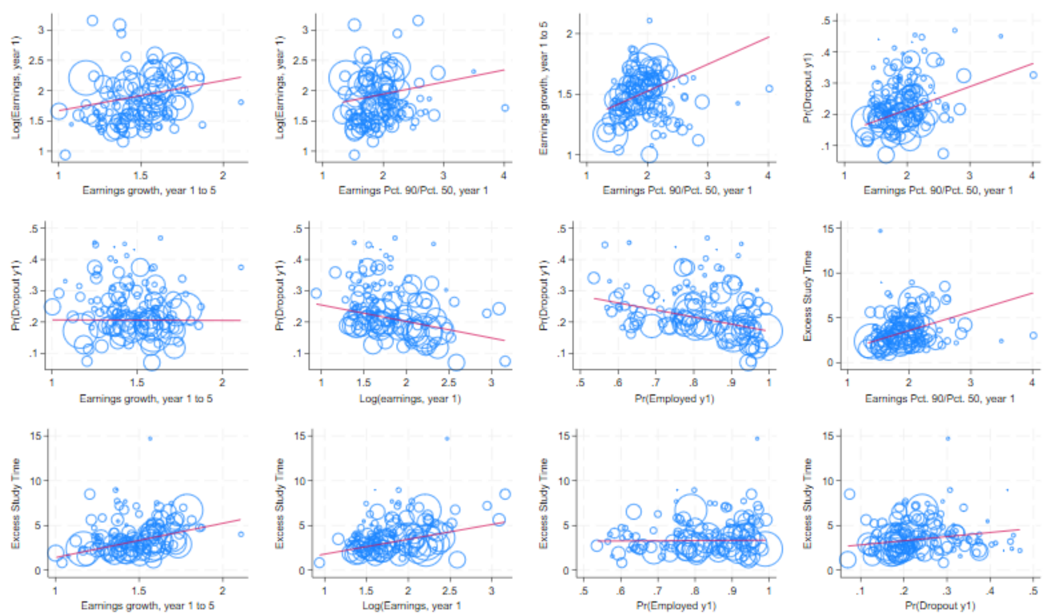
Note: The Figure shows average earnings five years after graduation, earnings growth over the first five years, the 90/50 earning ratio after one year, and the probability of being employed in the year following graduation, for the programmes chosen by PSU takers in one PSU point bins around the grant eligibility cut-off (normalised to zero across years and income quintiles).

Figure A12: Characterisation of Chosen Programme - Other Characteristics



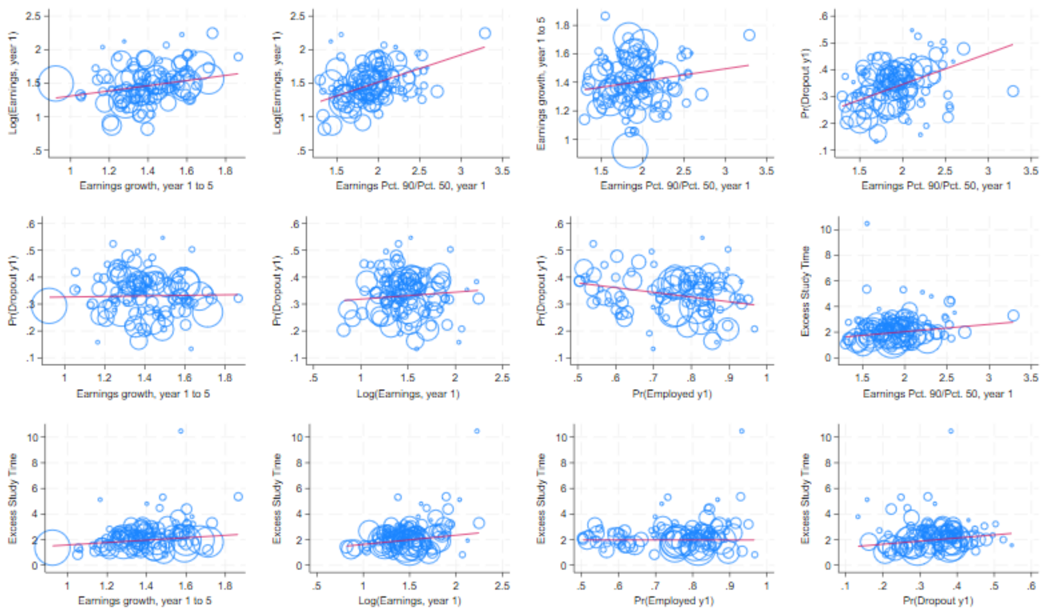
Note: The Figure shows average dropout rates after the first year of study, actual and realised time until graduation, and average tuition fees for the programmes chosen by PSU takers in one PSU point bins around the grant eligibility cut-off (normalised to zero across years and income quintiles).

Figure A13: Correlations of Programme Characteristics - Universities



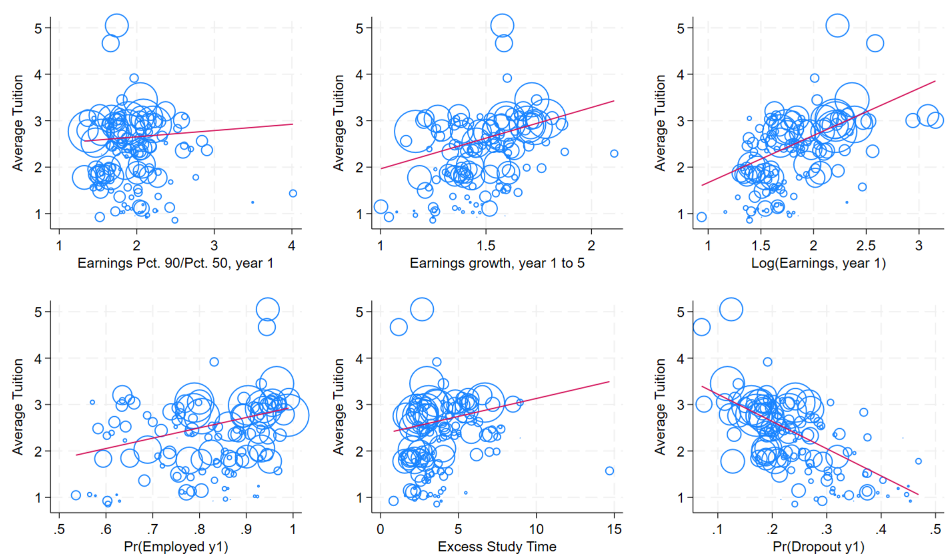
Note: The Figure displays scatter plots of pairs of programme characteristics for universities, together with their linear fit. Programmes are weighted by the number of enrollees.

Figure A14: Correlations of Programme Characteristics - Vocational Institutions



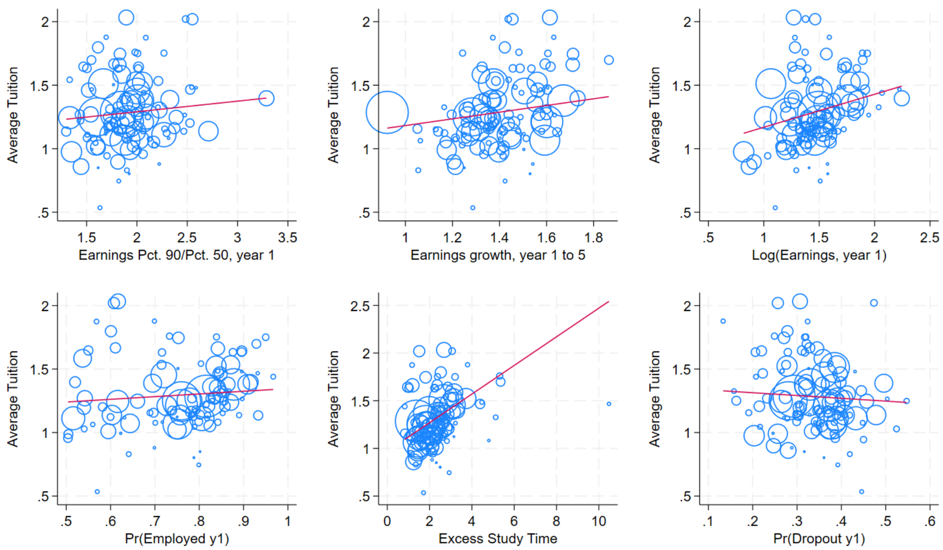
Note: The Figure displays scatter plots of pairs of programme characteristics for vocational institutions, together with their linear fit. Programmes are weighted by the number of enrollees.

Figure A15: Correlations of Programme Characteristics - Universities



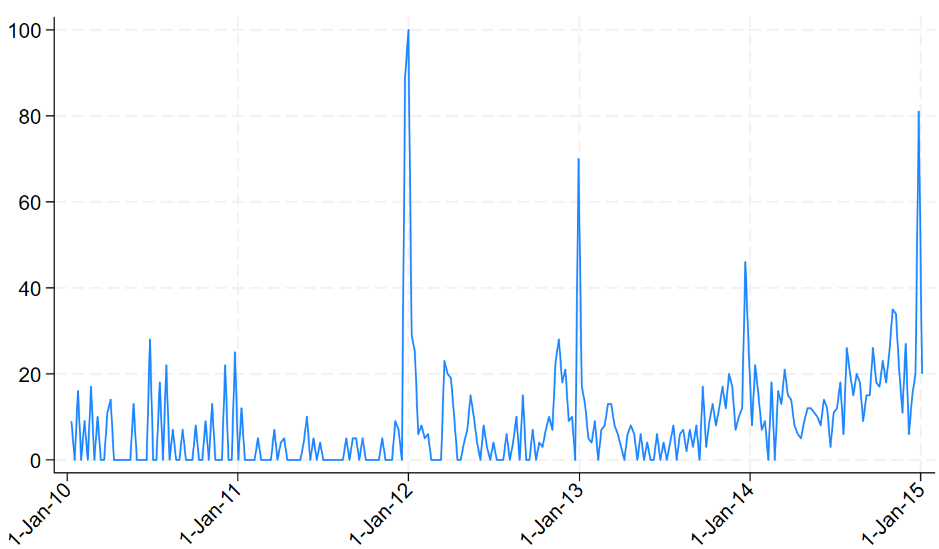
Note: The Figure displays scatter plots of a set of programme characteristics against tuition fees for universities, together with their linear fit. Programmes are weighted by the number of enrollees.

Figure A16: Correlations of Programme Characteristics - Vocational Institutions



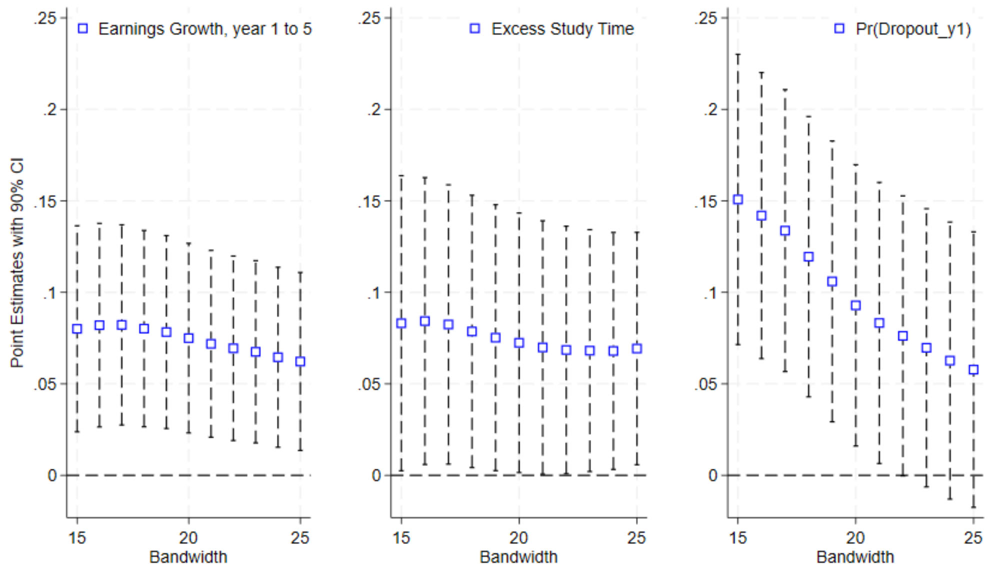
Note: The Figure displays scatter plots of a set of programme characteristics against tuition fees for vocational institutions, together with their linear fit. Programmes are weighted by the number of enrollees.

Figure A17: Weekly Search for MiFuturo Website: Period 2010-2015



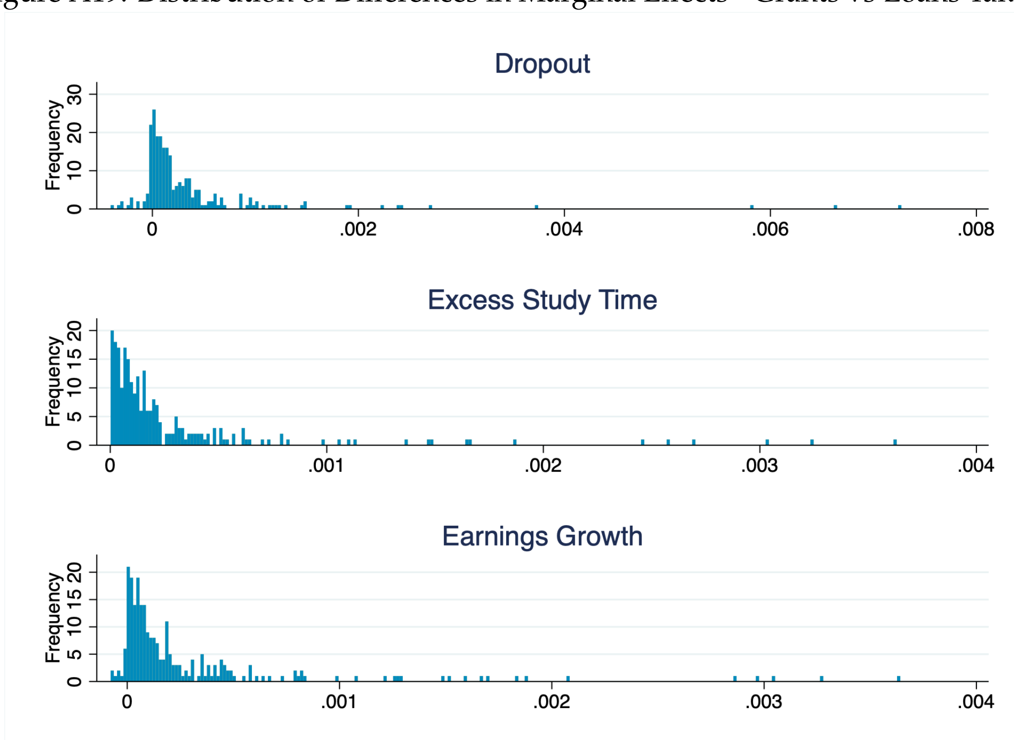
Note: The Figure displays the weekly Google Trend Index for MiFuturo searches in Chile over the period 2010-2015. The index ranges from 0-100, and it represents the relative search intensity compared to the week in which the Website was searched the most.

Figure A18: Differences in Valuation of programme Attributes (Δ_k) - Varying Bandwidths



Note: The Figure displays point estimates for Δ_k for three different programme characteristics and varying bandwidth choices. For details on the model estimation, see Section 4.1 of the main text; for other included covariates, see the tablenotes of Table 6.

Figure A19: Distribution of Differences in Marginal Effects - Grants vs Loans Takers



Note: The Figure displays the distribution of differences in marginal effects between grant holders and loan takers across the 246 programmes included in the discrete choice model. For details on the model estimation, see Section 4.1 of the main text; for other included covariates, see the tablenotes of Table 6.

B Additional Tables

Table B1: Effect of Grants vs. Loans on enrolment and STEM: Split Sample Period

	2008 - 2011		Full Sample	
	Enrolled	STEM	Enrolled	STEM
RD_Estimate	0.016*	0.008	0.023**	0.014**
	(0.008)	(0.006)	(0.006)	(0.005)
Bandwidth	35	68	31	47
Effective N	56,393	105,700	90,667	133,401

Note: ** $p < 0.05$, *** $p < 0.01$.
All dependent variables are binary indicators. Reference category for STEM: non-enrolment or enrolment in any other major. The table presents estimates for β_1 in equation (2) of the main text, splitting the sample into the periods 2008-2011 and 2008-2014, respectively. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Table B2: Effect of Grants vs. Loans: Non-STEM Fields

	Business & Management	Education	Social Science	Health
RD_Estimate	-0.006	0.000	0.008*	0.008
	(0.004)	(0.005)	(0.004)	(0.006)
Baseline Mean	0.109	0.106	0.066	0.163
Bandwidth	56	66	58	47
Effective N	70,125	81,231	72,555	59,758
	Arts & Architecture	Agriculture	Law	Humanities
RD_Estimate	-0.003	-0.002	-0.003	-0.002
	(0.002)	(0.002)	(0.003)	(0.001)
Baseline Mean	0.041	0.019	0.034	0.010
Bandwidth	58	83	53	74
Effective N	72,555	97,998	66,367	89,714

Note: ** $p < 0.05$, *** $p < 0.01$.
Dependent variables are binary indicators for choosing the respective fields. Reference category: non-enrolment or enrolment in any other major. The Table presents estimates for β_1 in equation (2) of the main text. Optimally chosen bandwidths according to Calonico *et al.* (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Table B3: Hypothetical and Observed Change in enrolment by Field at the Cut-off

	Below the cut-off (in %)	Hypothetical Change	Observed Change
	(1)	(2)	(3)
STEM	25.3	1.1	2.9
Business	10.7	0.4	-0.3
Education	10.0	0.4	0.7
Social Science	6.6	0.3	0.6
Health	16.5	0.7	0.6
Arts & Architecture	4.1	0.2	-0.3
Agriculture	2.0	0.1	-0.2
Law	3.4	0.1	-0.4
Humanities	1.0	0.04	-0.2
Non-enrolment	20.4	-3.3	-3.3

Note: Column 1 displays the distribution across fields and non-enrolment for PSU test takers who scored marginally below the grant eligibility cut-off (β_0 in equation (2) for a bandwidth of 41 – the optimal bandwidth for enrolment in STEM). In column (2) we present the changes by field that we should expect at the cut-off in a counterfactual scenario, in which all the additional enrolment in higher education (3.3%) sorted proportionally to the enrolled students below the cut-off - i.e., keeping major choices conditional on enrolment constant. Column (3) instead presents the actually observed changes (β_1 in equation (2) for a bandwidth of 41).

Table B4: Summary Statistics for Programme Characteristics across Alternatives

	Programmes at Universities				**Programmes at Vocational Inst.**			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Pr(Employed_y1)	0.843	0.112	0.345	0.991	0.734	0.140	0.226	0.967
Earnings_y1 (100,000 Ch.Pesos)	7.312	2.822	2.556	23.498	4.395	1.044	2.268	9.445
Earnings Growth, year 1 to 5	1.497	0.181	1.002	2.108	1.398	0.193	0.923	1.865
Earnings Pct.90/Pct.50, year 1	1.873	0.306	1.323	4.015	1.870	0.274	1.297	3.287
Pr(Dropout_y1)	0.206	0.059	0.070	0.469	0.330	0.067	0.133	0.547
Excess Study Time (in Semesters)	3.322	1.437	0.841	14.699	1.961	0.666	0.824	10.480
Formal Study Time (in Semesters)	9.812	1.597	4.000	14.026	6.370	1.809	4.000	9.626
Share of Female Students	0.530	0.229	0.000	1.000	0.527	0.290	0.000	0.999
Share Students from Subsidised School	0.521	0.076	0.241	0.765	0.547	0.069	0.239	0.771
Share Students from Public School	0.295	0.084	0.107	0.744	0.414	0.091	0.110	0.761
Business & Management	0.151		0	1	0.200		0	1
Agriculture	0.021		0	1	0.011		0	1
Arts & Architecture	0.032		0	1	0.033		0	1
STEM	0.222		0	1	0.330		0	1
Social Sciences	0.128		0	1	0.059		0	1
Law	0.056		0	1	0.009		0	1
Education	0.132		0	1	0.107		0	1
Humanities	0.012		0	1	0.011		0	1
Health	0.245		0	1	0.239		0	1

Note: The table presents summary statistics across the 246 programmes matched to students in our sample. 131 are university programmes, while the remaining are offered at vocational institutions. *Excess Study Time* is the time until graduation of an average graduate minus the formal time to graduation as specified in the study regulations. *Pr(Dropout_y1)* is the share of students dropping out after one year of study. *Pr(Employed_y1)* is the share of graduates in employment one year after graduation. The statistics are weighted by the number of enrollees.

Table B5: Shares of Programmes per Field in Different Institutions

	Universities	**Vocational**	**CRUCH**	**Private Univ.**
Share (%):				
Business/Management	11.0	23.6	8.1	13.2
Agriculture	2.5	2.7	3.0	2.1
Arts/Architecture	5.2	6.7	4.9	5.4
STEM:	27.8	36.9	40.4	18.0
Engineering	23.7	36.2	33.6	16.0
Natural Sciences	4.1	0.7	6.8	2.0
Social Sciences	11.7	5.9	8.3	14.3
Law	3.4	1.2	1.9	4.7
Education	19.1	9.6	19.0	19.2
Humanities	2.2	0.5	2.2	2.1
Health	17.3	13.0	12.4	21.0

Note: The Table displays the shares of each field among all programmes offered by the respective type of institutions in our sample years (2012 to 2014). The first column is the sum of all programmes offered at CRUCH universities and other private universities (columns 3 and 4).

Table B6: Distribution Other Characteristics - STEM vs no-STEM Intensive Institutions

	University		**CRUCH**	
	STEM Int.	No STEM Int.	STEM Int.	No STEM Int.
# of Enrollees	11910.97	9018.41	11728.46	10818.83
	(8984.66)	(8141.06)	(5746.52)	(7277.11)
% Professors with Ph.D	0.18	0.16	0.30	0.27
	(0.14)	(0.13)	(0.11)	(0.12)
% Professors with Master	0.31	0.34	0.30	0.33
	(0.13)	(0.12)	(0.09)	(0.11)
# of Professors	409.65	405.41	472.74	647.15
	(339.73)	(471.86)	(302.16)	(602.52)
Ratio Students to Professors	33.24	31.03	27.30	21.14
	(11.55)	(13.86)	(5.77)	(4.55)
Square Meters	73314.92	80946.48	82642.3	161549.3
	(50958.09)	(124389.2)	(36655.17)	(177683.4)
# Books (Thousands)	122.47	266.42	148.75	576.02
	(83.44)	(638.18)	(79.73)	(998.64)
# Computers	1285.90	893.09	1865.29	1677.29
	(1184.23)	(1293.85)	(1693.95)	(2033.07)

Note: The Table displays average values of each respective institution characteristic by institution type and STEM intensity (standard deviations in parentheses). We classify institutions as STEM-intensive if the share of students enrolled in STEM among all enrollees is above the median share across institutions. The data stems from the *buscador de instituciones*, provided by the *MiFuturo* initiative of the Ministry of Education. *#Books (Thousands)* and *# Computers* refer to the stock of each equipment type available to students.

Table B7: Heterogeneity in the Effects of Grants vs Loans by Institution Type

	(1) STEM × CRUCH	(2) STEM × Uni	(3) STEM × Vocational
RD_Estimate	0.020***	0.006**	0.001
	(0.006)	(0.003)	(0.004)
Bandwidth	39	57	44
Effective N	49,684	71,353	55,560

Note: ** $p < 0.05$, *** $p < 0.01$.
The Table presents estimates for β_1 in equation (2), using the interaction between a STEM dummy and institution-type indicators as outcomes. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Standard errors are clustered at the PSU test score level and reported in parentheses.

Table B8: Effect on Grants vs Loans - Conditional on Enrolment and Institution Type

	(1)	(2)	(3)
RD_Estimate	0.022***	0.021***	0.016**
	(0.008)	(0.008)	(0.007)
Bandwidth	54	51	57
Effective N	54,021	51,367	56,982
CRUCH Fixed Effect	No	Yes	No
Private Uni Fixed Effect	No	Yes	No
Institution Fixed Effects	No	No	Yes

Note: ** $p < 0.05$, *** $p < 0.01$.
The Table presents estimates for β_1 in equation (2), using an indicator for enrolment in a STEM programme as an outcome. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Standard errors are clustered at the PSU test score level and reported in parentheses. The estimation is based on the sample of enrolled students. Column (2) adjusts for CRUCH and Private University fixed effects, and column (3) for institution fixed effects (182). Here, institution refers to a specific university or vocational institution (e.g., Universidad de Chile).

Table B9: Heterogeneity in the Effect of Grants on General Enrolment

	Gender		
	Male	Female	Δ of Coefficients
RD_Estimate	0.030***	0.033***	0.003
	(0.009)	(0.011)	(0.014)
Baseline Mean	0.817	0.779	
Bandwidth	50	34	
Effective N	28,653	23,980	
	Parental Education		
	Fist-Gen	Second-Gen	Δ of Coefficients
RD_Estimate	0.031***	0.037***	0.006
	(0.009)	(0.013)	(0.016)
Basline Mean	0.798	0.797	
Bandwidth	34	39	
Effective N	24,957	21,601	
	Parental Income		
	Quintile 2+3	First Quintile	Δ of Coefficients
RD_Estimate	0.028***	0.053***	0.025
	(0.008)	(0.017)	(0.019)
Baseline Mean	0.800	0.785	
Bandwidth	34	42	
Effective N	36,102	9,820	

Note: ** $p < 0.05$, *** $p < 0.01$.
The Table presents estimates for β_1 in equation (2), separate by subgroups. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Standard errors are clustered at the PSU test score level and reported in parentheses.

Table B10: Covariate Balance around Grant Eligibility Cut-off, conditional on Enrolment

	Mean at cut-off (β_0)	RD Estimate (β_1)	Standard Error ($\hat{\beta}_1$)
High School GPA	5.731	0.006	0.009
# Working Family Members	1.158	-0.000	0.012
# Studying Family Members	0.102	-0.004	0.005
Female	0.529	0.004	0.009
Single Mother HH	0.192	-0.005	0.005
Academic Parents	0.444	-0.017	0.011
Took Science Test	0.663	0.001	0.010
Municipal School	0.273	0.010	0.008
Subsidised School	0.672	-0.019*	0.010
Academic School	0.810	-0.014*	0.008
Income quintile $\times$ year:			
Quintile 1 $\times$ 2012	0.171	0.010	0.016
Quintile 2 $\times$ 2012	0.116	-0.003	0.010
Quintile 3 $\times$ 2012	0.087	0.002	0.007
Quintile 2 $\times$ 2013	0.179	-0.006	0.021
Quintile 3 $\times$ 2013	0.124	-0.010	0.012
Quintile 2 $\times$ 2014	0.192	0.002	0.024
Quintile 3 $\times$ 2014	0.130	0.006	0.013
Region:			
Far North	0.060	-0.005	0.005
Near North	0.071	-0.005	0.005
Central	0.715	0.010	0.007
Near South	0.136	-0.002	0.005
Far South	0.015	-0.001	0.002

Note: The Table presents estimates for β_0 and β_1 in model (2), treating the respective socio-demographic variables as outcome. See notes of Table 2 for a description of the variables. All regressions are estimated on the sample of enrolled students. $^*p < 0.10$.

C Choice Set Changes Around Grant Eligibility Cut-Off

In this Appendix section, we present evidence for why our regression-discontinuity analysis cannot include observations for which the relevant PSU cut-off for grant eligibility is 500 points. This excludes all observations from 2015 and the lowest 20% of the income distribution in 2013 and 2014 from our main study sample (see Table 1 and the discussion in Section 2.2). The central argument is that a subset of Chilean universities, including all CRUCH institutions and a few additional private universities, participate in a centralised admission system, which partially relies on PSU scores for admission and matches students and programmes (institution $\times$ major combinations) following a Deferred Acceptance algorithm.[37] As we show below, the setting of this admission system creates a second treatment besides grant eligibility coinciding with the 500 PSU test score threshold: a change in students' choice sets.

Admission is based on two components. First, a score which we call programme score (PS) and which is calculated as a weighted average of high school gpa, relative performance within the high school graduating cohort, and all sub-components of the PSU test – including the mandatory math and language components that are used to determine grant eligibility, but also the voluntary components of science or history. The relative weights for the PS are programme-specific.[38] Second, programmes can require students to fulfil minimum requirements in terms of the unweighted math-language average PSU score and the PS. In Figures C1 and C2, we plot the histogram of programme-specific minimum requirements for each year of our analysis. As we can see, while only a subset uses minimum requirements on the PS, every programme imposes minimum PSU requirements.[39] It is worth noticing that, due to the presence of capacity constraints, passing the minimum PS score might not be sufficient for admission. Therefore, admission rules based on minimum scores would not bind in the case of competitive programmes, yet they do so in less-demanded programmes.

Using administrative data on decision weights used by each programme and information about admitted students, we determine realised admission thresholds for each programme. By definition, they correspond to the score of the last admitted student. With this information, we construct hypothetical choice sets for each student in our sample, taking into account both

[37] See Table C1 for an overview of the number of programmes participating in the central admission system and Larroucau and Rios (2020) for a detailed discussion of the algorithmic implementation of admission in Chile.

[38] High school rank has been introduced as a mandatory component to determine the programme score only in 2012.

[39] Admission rules became stricter over time. For example, the fraction of programmes requiring 500 as the minimum PSU score more than tripled between 2010 and 2011.

realised thresholds and minimum requirements. Figure C3 plots the average number of available programmes in students' choice sets as a function of the math-language PSU score used to determine grant eligibility. Students experience discontinuous changes in the dimension of their choice sets, corresponding to PSU values used as minimum admission requirement.[40] Importantly for our analysis, from 2013 onward, one of the cut-offs driving a discontinuous change in the choice set coincides with the grant eligibility cut-off of 500.

This would not be a problem by itself if we conjectured that the number of available options alone does not influence enrolment decisions. However, students who are marginally eligible for a grant also experience a change in the composition of fields in their choice sets. Similarly to Figure C3, in Figure C4, we plot the average shares of options from each respective field included in the choice set of students. As we can see, the share of STEM programmes discontinuously decreases at 500, at the expense of an increase in the share of education programmes. It is reasonable to argue that we are in the presence of different relevant treatments happening at the 500 cut-off. Disentangling the two is not possible in a regression-discontinuity analysis, and we consequently exclude the respective individuals from our sample.

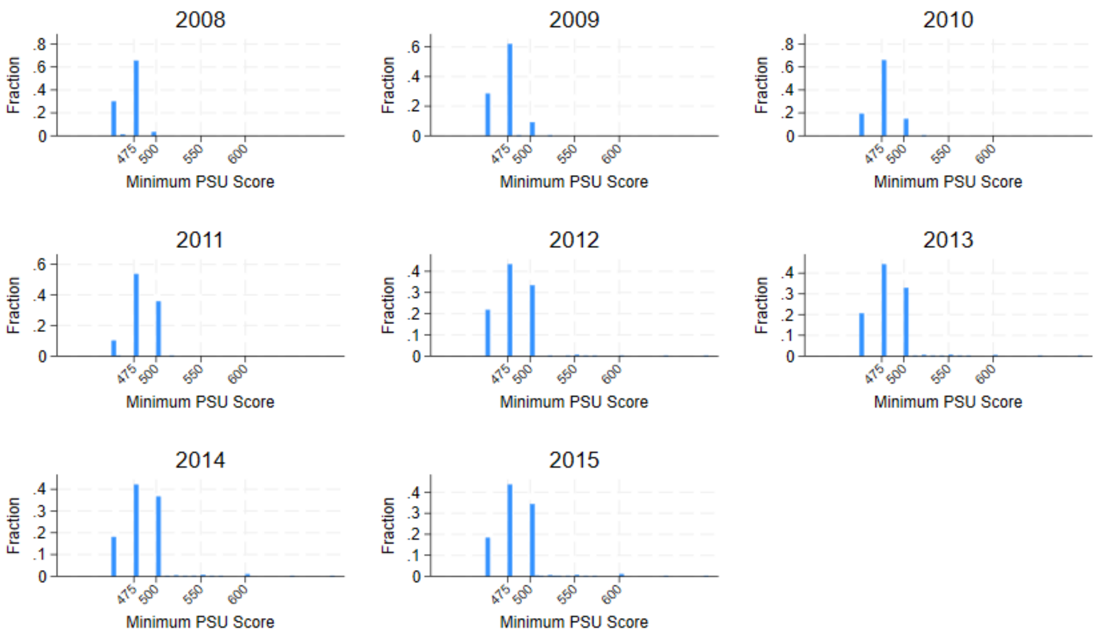
Table C1: Shares of programmes per field participating in the centralised system

	2008	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*
Total Number	945	938	960	976	1320	1374	1398	1413
Share (%):								
Business/Management	6.2	6.3	6.5	6.7	7.3	7.6	7.4	7.4
Agriculture	4.2	4.3	4.2	3.6	3.0	2.6	2.4	2.3
Arts/Architecture	5.5	5.4	5.3	5.0	5.7	5.5	5.4	5.5
STEM	37.6	37.1	37.9	38.3	33.6	34.5	34.1	33.5
Social Sciences	10.1	9.8	9.5	9.2	10.6	10.6	10.9	11.1
Law	2.0	2.0	2.0	1.9	2.7	2.6	2.7	2.6
Education	20.8	21.2	20.9	21.1	19.1	18.5	18.2	18.8
Humanities	2.3	2.5	2.2	2.4	2.9	2.8	2.5	2.5
Health	11.2	11.4	11.6	11.8	15.1	15.3	16.2	16.3

Note: The Table displays the number of all programmes participating in the centralised admission system from 2008 to 2015, as well as the share of each of our 9 aggregated fields of study among the programmes.

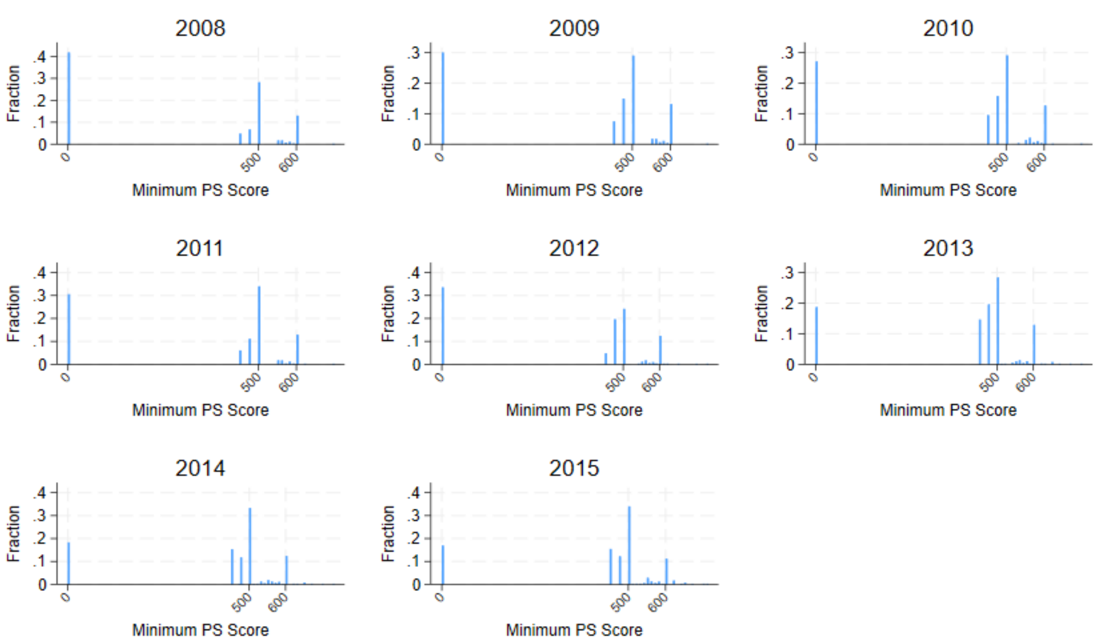
[40]Note that we can conclude from this observation that de facto thresholds imposed by capacity constraints are not systematically larger than minimum entry requirements. Otherwise, we would have observed a smoother change in the dimension of the choice set.

Figure C1: Distribution of minimum PSU requirements over the years



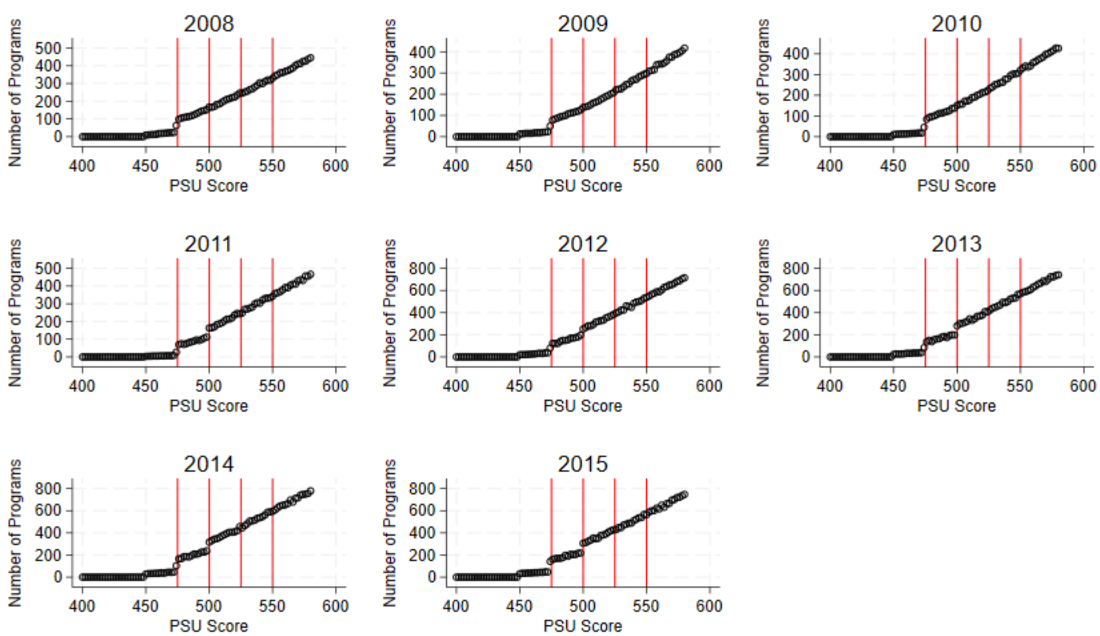
Note: The Figure shows the minimum PSU admission requirements across programmes.

Figure C2: Distribution of minimum PS requirements over the years



Note: The Figure shows the minimum PS admission requirements across programmes.

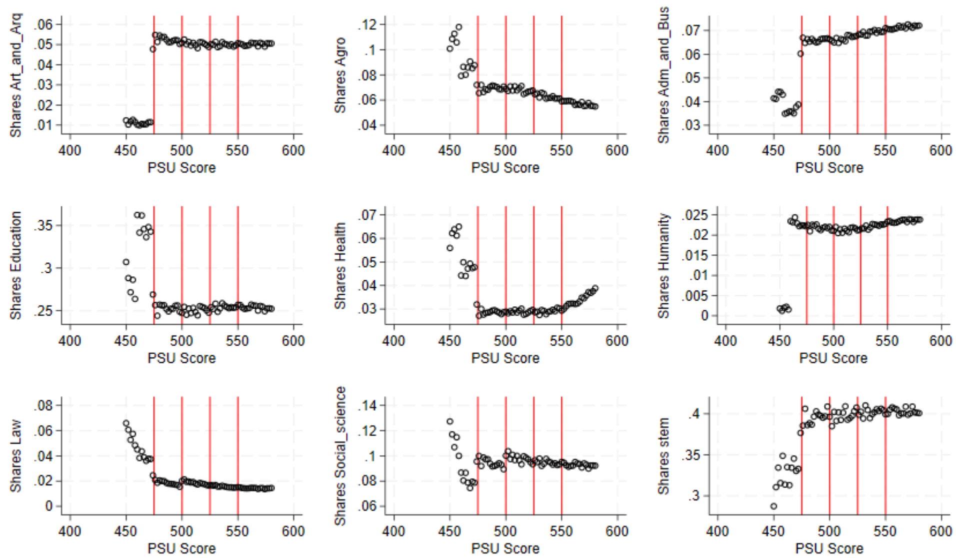
Figure C3: Number of programmes in the choice set as a function of PSU



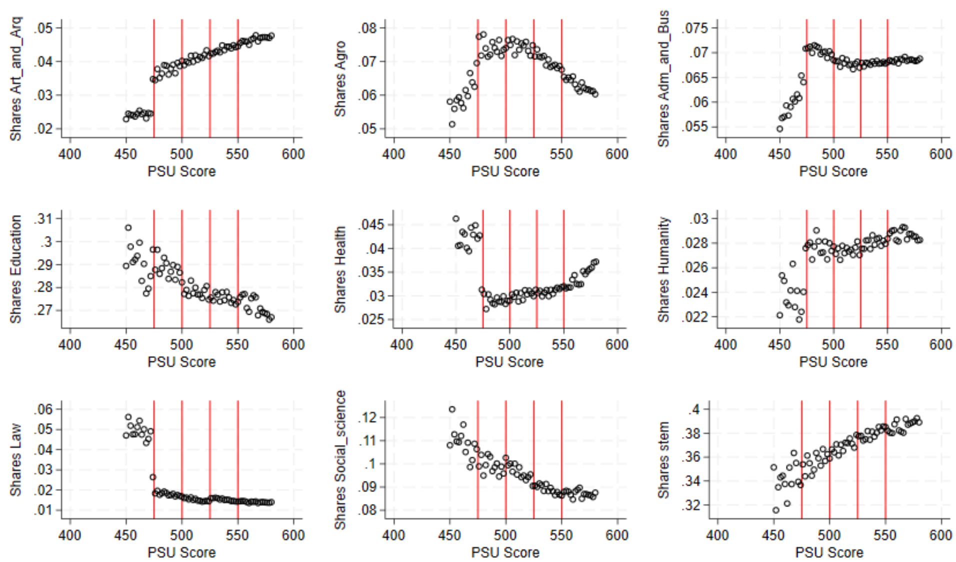
Note: The Figures show the average number of available programmes in students' choice sets as a function of PSU scores – PSU bins correspond to one point. The red lines refer to PSU scores of 475, 500, 525, and 550. The first threshold corresponds to eligibility for student loans. The last three are used for grant assignment (see also Table 1).

Figure C4: Shares of fields in the choice set as a function of the PSU score

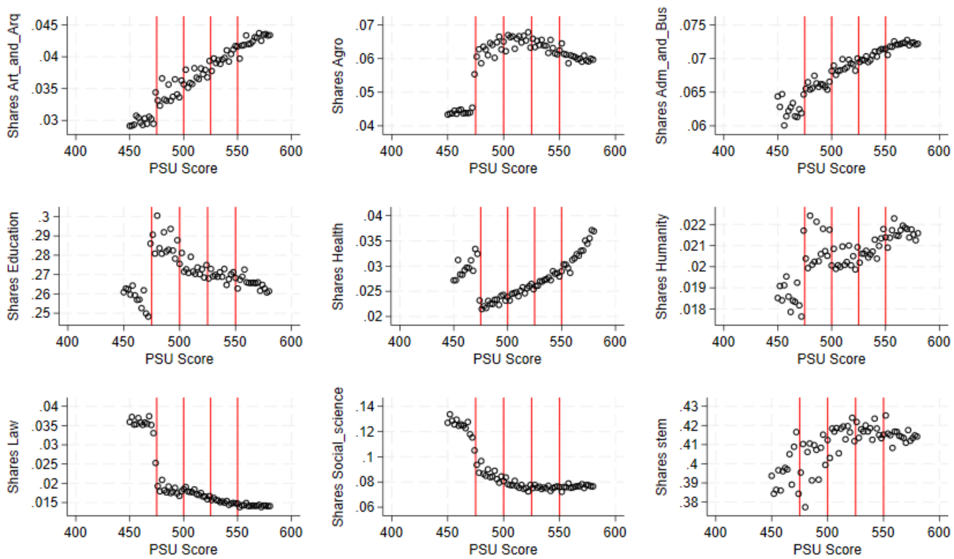
2008



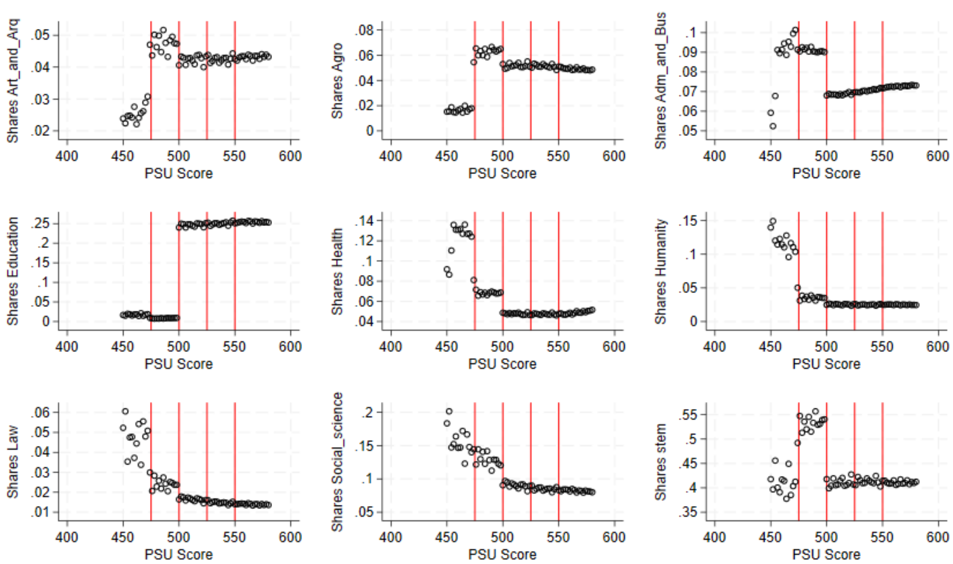
2009



2010


Shares Art_and_Arq
PSU Score
Shares Agro
PSU Score
Shares Adm_and_Bus
PSU Score
Shares Education
PSU Score
Shares Health
PSU Score
Shares Humanity
PSU Score
Shares Law
PSU Score
Shares Social_science
PSU Score
Shares stem
PSU Score

2011


Shares Art_and_Arq
PSU Score
Shares Agro
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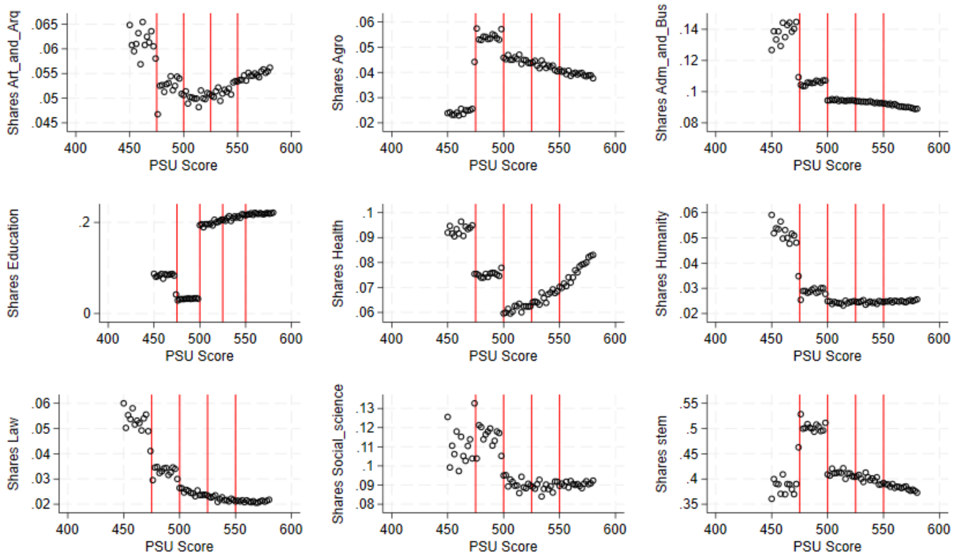
Shares Adm_and_Bus
PSU Score
Shares Education
PSU Score
Shares Health
PSU Score
Shares Humanity
PSU Score
Shares Law
PSU Score
Shares Social_science
PSU Score
Shares stem
PSU Score

2012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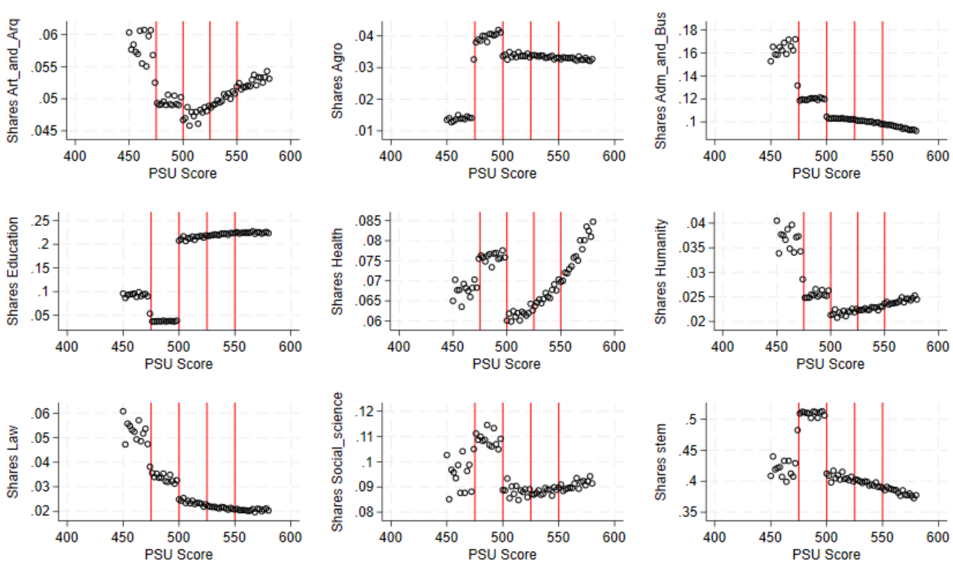
PSU Score
Shares Law
PSU Score
Shares Social_science
PSU Score
Shares stem
PSU Score

2013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Shares Education
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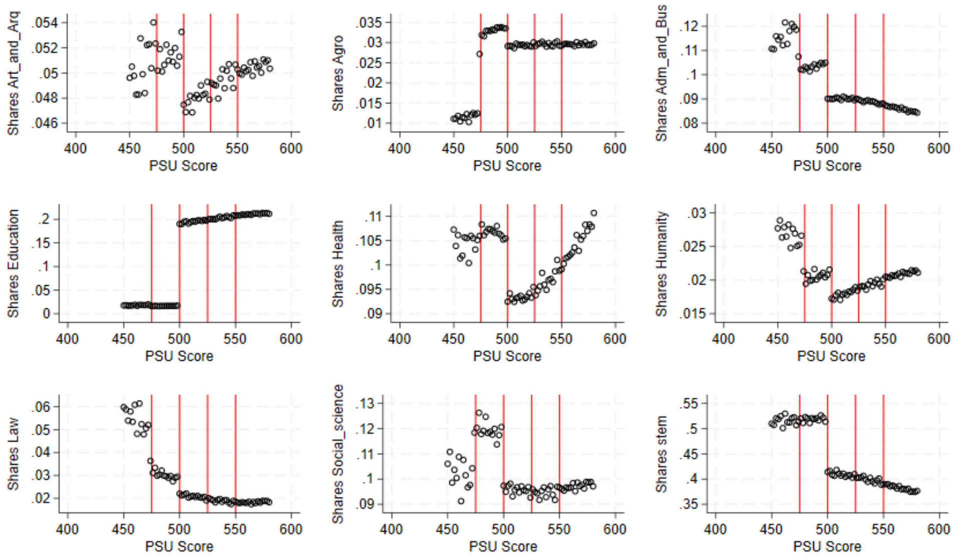
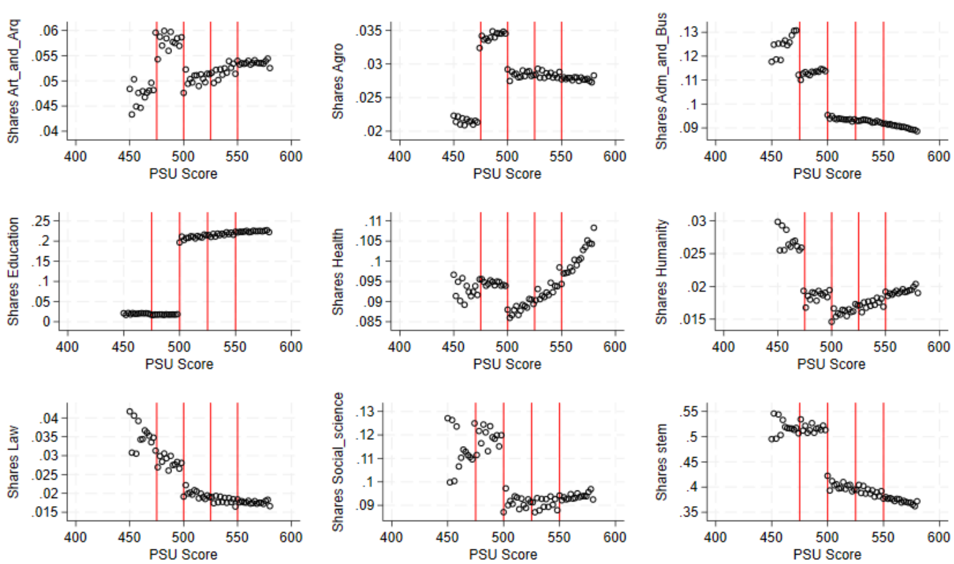
Shares Law
PSU Score
Shares Social_science
PSU Score
Shares stem
PSU Score

2014



2015



Note: The Figure shows the average shares of the nine fields of study among available programmes in students' choice sets as a function of PSU scores – PSU bins correspond to one point. The red lines refer to PSU scores of 475, 500, 525, and 550. The first threshold corresponds to eligibility for student loans. The last three are used for grant assignment (see also Table 1).

D Heterogeneous Treatment Effects in the RD Framework

We explore heterogeneity in the effect of financial aid on enrolment in STEM along three socio-demographic dimensions: gender, parental education, and parental income. Additionally, we consider heterogeneity by the two cut-off values of 525 and 550 PSU points, respectively, and by cohort (PSU test-takers in the years 2012, 2013, and 2014). To do so, we re-estimate model (2) separately for each of our considered subgroups.

Socio-Demographic Heterogeneity. Table D1 presents the point estimates by socio-demographic subgroup, i.e., female and male students, students with at least one parent with an academic degree and students whose parents have no academic degree, as well as students coming from a family in the bottom income quintile and students from quintiles two and three.[41] For each group, we choose optimal data-driven bandwidths (Calonico *et al.*, 2020). The third column tests for differences in the effect sizes.

Point estimates are smaller for female than for male students, for people whose parents have a higher education degree, and for students from relatively higher-income families. Note that we cannot reject the null hypothesis of equal effect sizes for male and female students. This result is particularly interesting given the vastly different baseline enrolment rates in STEM across genders. While only 13% of marginally ineligible female students enrol in STEM fields, almost 40% of male students do. Relative to these baseline Figures, grant eligibility actually increases STEM enrolment more strongly for female than for male students. For female students, the effect corresponds to a 15% change relative to the baseline. Tables D2 and D3 repeat the heterogeneity analysis, splitting STEM into engineering and science majors. Doing so reveals that female students are considerably more likely to use grants to enrol in science degrees, whereas male students adjust by choosing engineering more frequently.

Contrary to the case of gender, baseline enrolment rates in STEM differ little between students coming from either the poorest family income quintile or from quintiles two and three. In terms of education, we see a similar picture. Also, here, baseline enrolment rates are comparable. We do not find evidence of differential effects for both dimensions of heterogeneity. Students from relatively poorer and less educated families appear to react slightly more sensitively to becoming eligible for a grant. However, the differences are muted even relative to gender differences, and our data does not allow us to reject the null hypothesis of equal effects across groups.

[41] Recall that students from the top two income quintiles are not eligible for grants in any of the years we consider.

Table D1: Heterogeneity in the Effect of Grants on Enrolment in STEM

	Gender		
	Male	Female	Δ of Coefficients
RD_Estimate	0.042***	0.020**	-0.022
	(0.013)	(0.008)	(0.015)
Baseline Mean	0.398	0.130	
Bandwidth	49	39	
Effective N	28,167	27,210	

	Parental Education		
	First-Gen	Second-Gen	Δ of Coefficients
RD_Estimate	0.033***	0.025***	-0.008
	(0.010)	(0.009)	(0.013)
Baseline Mean	0.252	0.251	
Bandwidth	39	53	
Effective N	28,344	28,202	

	Parental Income		
	Quintile 2+3	First Quintile	Δ of Coefficients
RD_Estimate	0.028***	0.034**	0.006
	(0.008)	(0.017)	(0.019)
Baseline Mean	0.255	0.243	
Bandwidth	41	56	
Effective N	42,475	12,969	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Reference category for STEM: non-enrolment or enrolment in any other major. The table presents estimates for β_1 in equation (2), separate by subgroups. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Table D2: Heterogeneity in the Effect of Grants on Enrolment in Engineering

	Gender		
	Male	Female	Δ of Coefficients
RD_Estimate	0.042***	0.008	-0.034**
	(0.013)	(0.007)	(0.015)
Baseline Mean	0.376	0.109	
Bandwidth	47	46	
Effective N	27,354	31,485	

	Parental Education		
	First-Gen	Second-Gen	Δ of Coefficients
RD_Estimate	0.029***	0.017*	-0.012
	(0.010)	(0.010)	(0.014)
Baseline Mean	0.230	0.230	
Bandwidth	43	56	
Effective N	31,130	29,608	

	Parental Income		
	Quintile 2+3	First Quintile	Δ of Coefficients
RD_Estimate	0.022***	0.029*	0.007
	(0.007)	(0.015)	(0.017)
Baseline Mean	0.234	0.223	
Bandwidth	43	65	
Effective N	45,054	14,897	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Reference category for Engineering: non-enrolment or enrolment in any other major. The table presents estimates for β_1 in equation (2), separate by subgroups. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Table D3: Heterogeneity in the Effect of Grants on Enrolment in Science

	Gender		
	Male	Female	Δ of Coefficients
RD_Estimate	-0.000	0.011^{***}	0.011^{***}
	(0.003)	(0.003)	(0.004)
Baseline Mean	0.022	0.019	
Bandwidth	60	40	
Effective N	33,815	27,878	

	Parental Education		
	First-Gen	Second-Gen	Δ of Coefficients
RD_Estimate	0.003	0.008^{*}	0.005
	(0.003)	(0.004)	(0.005)
Baseline Mean	0.022	0.020	
Bandwidth	49	52	
Effective N	35,323	27,916	

	Parental Income		
	Quintile 2+3	First Quintile	Δ of Coefficients
RD_Estimate	0.004^{*}	0.006	0.002
	(0.003)	(0.005)	(0.006)
Baseline Mean	0.021	0.02	
Bandwidth	52	49	
Effective N	53,012	11,325	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Reference category for Science: non-enrolment or enrolment in any other major. The table presents estimates for β_1 in equation (2), separate by subgroups. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico *et al.* (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Heterogeneity by Cut-off and Cohort. Our main analysis is based on a normalised grant eligibility cut-off, pooling over individuals and ignoring that the underlying necessary PSU test score value differs by year and family income quintile (see Table 1). Since each individual is assigned a unique cut-off value and not exposed to several cut-offs, this is unproblematic (Cattaneo *et al.*, 2016). Nonetheless, one could be interested in heterogeneity for students with varying cut-offs. Cattaneo *et al.* (2021b), for instance, present an extrapolation framework that uses different cut-off values to generalise the RD estimate for arbitrary values of the running variable within the range of observed cut-offs.

Table D4 presents the point estimates obtained when estimating the RD model separately for the two subgroups with varying cut-offs. STEM enrolment increases by 4.2 percentage points for students with a PSU test-score threshold of 525, whereas the estimated discontinuity is 2.5 percentage points for students further up in the PSU test-score distribution. At first glance, we might infer that the effect of grant eligibility on STEM enrolment is decreasing in students' academic preparedness as measured by the PSU test score. However, we cannot reject the null hypothesis of equal effects for the two groups. Moreover, the assumptions underlying the approach to extrapolation suggested by Cattaneo *et al.* (2021b) would imply that the relationship between the PSU test result and STEM enrolment is the same for both groups below the first cut-off of 525. For us, this is not the case, suggesting that there are systematic group differences that do not allow us to exploit the multi-cut-off setting for generalisations.

This could partially reflect treatment effect heterogeneity over time, as illustrated in columns (3) to (5) of Table D4. For all PSU test takers in 2012, the relevant grant eligibility cut-off was 550. The effect at the 525 cut-off is consequently an average of parts of the cohorts 2013 and 2014, and for the latter group, the effect of grant eligibility on STEM enrolment is reduced. While we do not have strong evidence on why the effect is lower among cohort 2014, we can speculate that the lower treatment might partially reflect the anticipation of tuition fee reductions that were implemented in 2015.

Table D4: Heterogeneity in the Effect of Grants on Enrolment in STEM

	Cohort				
	2012	2013	2014	$\Delta_{2012-2014}$	$\Delta_{2013-2014}$
RD_Estimate	0.031**	0.036***	0.013	0.018	0.023
	(0.014)	(0.013)	(0.012)	(0.018)	(0.018)
Baseline Mean	0.235	0.261	0.276		
Bandwidth	57	46	60		
Effective N	28,358	17,405	22,396		

	Cut-off		
	525	550	$\Delta_{525-550}$
RD_Estimate	0.042***	0.025***	0.017
	(0.012)	(0.009)	(0.015)
Baseline Mean	0.260	0.247	
Bandwidth	36	53	
Effective N	16,576	42,688	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The Table presents estimates for β_1 in equation (2), separate by subgroups. All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Standard errors are clustered at the PSU test score level and reported in parentheses.

E Data Appendix: Merging Students with Programme Information from *Mi Futuro*

MiFuturo contains information on 206 programmes (institution type × major combinations). Using this information, we can match 89.3% of the enrolled students in our sample to programme-specific information. We can decrease the loss of information coming from not matching all students in our sample by imputing characteristics of some of the programmes chosen by non-matched students. This allows us to match 94.5% of our sample to a total of 246 programmes. To do so, we apply the following procedures:

1. Some students are not matched because they enrol in so-called *Bachillerato* programmes ($\approx$ 1.5% of our sample). *Bachillerato* programmes are two-year preparatory academic programmes offered by universities and aimed at students wanting to explore different academic fields before choosing an explicit undergraduate major. While a *Bachillerato* allows for more flexibility than other explicit college majors, there are five broad types, each of which has more or less clear university career trajectories: Arts, Social Science, Humanities, and Health. We use data from cohorts 2008 to 2011 to understand the transitions of past graduates to different college majors after having finished the two-year preparatory programme of the *Bachillerato*. We then use these transition probabilities to create weighted averages of the characteristics of each of the follow-up programmes and assign them as values to students enrolled in a given *Bachillerato*. In the model, we treat them as a separate category besides the nine aggregate fields of study included as fixed effects.

2. Some students in our sample enrol in specific college majors, e.g., *Ingeniería en Alimentos* for which *MiFuturo* contains information for a given institution type but not for others. If we see that this leads to the exclusion of a student in our sample, we use information from the same major in different institution types for imputation. Specifically:

   (i) If we have non-missing information for a specific major in one type of vocational higher education institution (*Instituto Profesional (IP), Centro de Formación Tecnica (CFT)*) but not the other, we use this information directly for imputation. For 1.5% of our sample, we can use information from CFT programmes to impute missing data in IP programmes. For 0.5% of our sample, we can use the reverse case.

   (ii) If the information is missing either at the university level or for both vocational higher education types, the imputation is not as straightforward, given that there are consistent quality differences. In this case, we first use the non-missing information to calculate a scaling factor $\beta_k^{t,t'}$ for combinations of institution types $t \in \{University, IP, CFT\}$ and programme characteristics k. For instance, $\beta_{Earnings}^{Uni,IP}$ relates to the factor by which average earnings differ between universities and IPs across all majors. We then consider a programme characteristic x_{mtk}, where m refers to a specific major (in our model, j is the combination of m and t) and impute:

$$x_{mtk} = \beta_k^{t,t'} x_{mt'k}.$$

E.g., we use the information on earnings in a given major offered at a university to impute the discounted earnings in the same major in a CFT. Overall, we impute information for 1.2% of our sample enrolled in majors at IPs from majors in universities. For 0.5% of our sample, we use information from either IPs or CFTs to impute information for students enrolled in universities.