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

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Abstract

Using administrative data from Chile, we analyze whether financing higher education through student loans or grants affects college major choices of prospective university students. We exploit institutional arrangements that allocate either type of financing based on a standardized test to locally identify exogenous variation in access. Students that are marginally eligible for grants are more likely to enroll in STEM-related fields. Relying on information from past graduates on narrowly defined college programs, we provide evidence that this effect is more generally driven by grants acting as insurance mechanism against uncertainty about degree completion.

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1 Introduction

College majors differ substantially in aspects such as expected labor market earnings, employment probabilities, and their ex ante likelihood of degree completion. Contrasting high return majors from low return majors for instance reveals differences in earnings comparable to the overall college wage premium (Altonji, Blom and Meghir, 2012). The question of which major to enroll 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 labor market outcomes. At the same time, they might disincentivize 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 there is a positive correlation between degree completion uncertainty and favorable labor market prospects 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 financing their higher education with grants and those that need to rely on student loans, but also by disentangling the relative contribution of program-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 centralized 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.

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

Using administrative data on individual-level college enrollment and PSU test results for the 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. A particularly interesting group of subjects to focus on are science, technology, engineering, and mathematics (STEM) majors, since – as we show below – they are an example for majors that are characterized by high mean monetary returns and employment probabilities, but also by high drop out rates and earnings uncertainty. We observe an increased enrollment of 12.5% (3 percentage points) in STEM fields for students that are marginally eligible for grants. While there is some heterogeneity with respect to the socio-economic background of students, effects are of comparable magnitude and positive for each subgroup we consider. The second group of majors for which we document an increased enrollment around the cut-off, albeit less precisely estimated, are the social sciences (by 12%). Interestingly, the estimates of Hastings, Neilson and Zimmerman (2013) point in the direction that both STEM and social science majors offer particularly high economic returns in Chile.

The fact that we see increased enrollment in high monetary return fields such as STEM allows us to rule out that more generous financial aid leads students to choose lower return fields on average. This highlights our notion that a thorough understanding of the link between financial aid and college major choices requires a more nuanced description of major characteristics that goes beyond comparisons of expected returns. To make progress in that direction, we use data from *MiFuturo*, an initiative by the Chilean ministry of education, which collects information of past graduates for narrowly defined higher education programs (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 program-specific aspects such as employment probabilities (one and two years after graduation), 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 this program-level information to estimate a discrete college major choice model on students within a narrow bandwidth around the grant eligibility cut-off. The results of this exercise indicate that students that are marginally eligible for grants are less concerned about dropout rates and excessive times until degree completion in their preferred programs than students marginally below the cut-off. This is the case also conditional on labor market outcomes (mean earnings, variance of earnings, employment probabilities), which themselves are not valued differently by students with access to different types of financial aid. Additionally including fixed effects for nine aggregate fields of study, allows us to consider variation in dropout rates *within* STEM degrees. This implies that our results pointing in the direction of grants acting as an insurance mechanism are more general, and that our more aggregated regression-discontinuity results pick up the high dropout rates that are associated with STEM degrees. In fact, conditional on the considered program-level characteristics, students with either loans or grants do not seem to value STEM degrees differently.

Contrary to our results, a small literature focusing 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 (Andrews and Stange, 2019; Stange, 2015; Cornwell, Mustard and Sridhar, 2006; Rothstein and Rouse, 2011; Sjoquist and Winters, 2015; Stater, 2011; Hampole, 2022). We complement and extend this earlier literature by studying a financial aid setting that is harmonized across an entire country, and by explicitly disentangling the influence of many correlated program characteristics and their interaction with financial aid. Relying on large administrative records and a discrete choice model, we thereby show that labor market concerns are only a subset of relevant program characteristics, which need to be adjusted for in order to appropriately characterize the driving forces behind the effect of financial aid on students' choices. We do find that uncertainty about degree completion is a more relevant channel in our setting than labor market prospects of various degrees.

One key difference between the U.S. and Chile is that in the latter system student loans have an income-contingent component by default (see Section 2 for details).[2] The alternative to grants is therefore a loan system that already provides some insurance against labor market risks, which is typically argued to be a key feature of optimal student loan arrangements (Britton, van der Erve and Higgins, 2019; Lochner and Monge-Naranjo, 2016). For this reason, we might see muted differences between students with either grants or loans in terms of revealed preferences for labor-market characteristics. Student loans, even if income-contingent, provide much less insurance, however, for study-related risk such as dropout or a long time until degree completion.[3]

[2]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 labor market returns to college over vocational institutions (Bucarey, Contreras and Muñoz, 2020) or to various majors (Hastings, Neilson and Zimmerman, 2013), the role of financial aid in the decision to enroll in college (Solís, 2017), to dropout over time (Card and Solis, 2022) and for labor market outcomes (Solís, 2021), as well as the effectiveness of preferential admission policies (Tincani, Kosse and Miglino, 2022).

[3]In this way our results are also informative for the exercise conducted by Christiansen, Joensen and Nielsen (2007). The authors consider college major choices through the lens of a risk-return trade-off and classify choices as inefficient in an investment sense, if alternatives exist that would have allowed for either a higher income at a lower variance or a

Given our emphasis on study-related risk, one potential concern is that students entering more challenging fields because of grants might be negatively selected. In a final exercise, we therefore 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 programs. Thus, while the access to grants does shift students' college major choices, it does not seem to nudge students with particularly overoptimistic beliefs into demanding majors.[4]

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 in 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.

2.1 Institutional Setting

Until recent years the higher education system of Chile was characterized by relatively high tuition fees compared to other OECD countries.[5] For our study sample, students at the tenth percentile of

lower variance at the same income. We highlight that study-related uncertainty is an additional unobserved factor that is both relevant when considering the returns to a given college major and that is a significant driver of individuals' choices.

[4]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, Wiswall and Zafar, 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 – as is the case in our setting of policy-induced changes in the price of all majors.

[5]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.

the tuition fee distribution pay a yearly fee of approximately $1800, whereas the median student pays $3000. For comparison, the yearly median household income over the same period is roughly $5600. Only a few students can consequently afford to fully cover the costs of their studies on their own and the majority requires 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 standardized nation-wide 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 form of a loan or in form of a grant.

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 nation-wide 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 standardized 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 result necessary to obtain a grant is not constant over time, since the access to grants has been extended between 2011 and 2015. Table 1 summarizes 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 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 Table 1 also illustrates that the source for financing of grants differs by institution type. The Chilean higher education system is broadly divided into two groups of institutions. The first group consists of the so-called traditional universities that are part of a network called

Table 1: PSU Threshold for Grant Eligibility

Bicentennial and Juan Gomez Millas (JGM)					
	$2008-2011^{*}$	*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
Decile 7	N.E.	N.E.	N.E.	N.E.	500
Decile 8	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 either of the two grants, by year and family income quintile. N.E.: not eligible. Bicentennial and JGM grants are received conditional on enrolling in CRUCH and accredited universities, respectively.
$*$ JGM was introduced in 2012.

CRUCH and typically considered to be of higher prestige.[6] Conditional on meeting the income and PSU requirements, students enrolled at a CRUCH university are eligible to the *Beca Bicentenario* or Bicentennial Grant (BG), covering up to 90% of reference tuition. The second group of higher education providers includes all other private universities and vocational institutions. As outlined in Table 1, eligible students at the latter schools are financed through the *Beca Juan Goméz Millas* (JGM), which covers up to $2000 of yearly tuition.

Irrespective of the institution type, any student that is marginally ineligible for a grant in terms of his or her test score is still eligible for a subsidized student loan. This implies that students close to the PSU threshold have access to either types 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 has more favorable 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 subsidizing the CAE, making it more comparable to the FSCU both in terms of

[6]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.

interest rates (now 2%) and income contingent repayments (cap at 10% of income).

While grants and loans are institution-specific, they differ little between majors.[7] That is, conditional on studying at a given university, an economics-major and an engineering-major are eligible to similar amounts of funding. This is in line with pricing behavior 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, individual programs seem to be priced rather homogeneously.[8] In Section 3.2 we provide further information on the set of majors offered by universities and vocational institutions, and demonstrate that, while financial aid is correlated with institution type, the supply of majors is not. We can consequently focus on students' choices and study the effect of financial aid on the demand of college majors without having to worry about supply-driven differences.

In line with most European countries, students in Chile enroll immediately in a given institution-major combination and do not choose their field of study after enrolling. They do so after having received their PSU test result and thus fully aware of which type of funding they will be able to access.

2.2 Data and Sample Construction

Through DEMRE 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 to administrative records of the Chilean ministry of education. This way we are able to obtain rich socio-demographic information on family background, gender and academic performance in high school, as well as enrollment 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 and recent high school graduates in the respective academic year, (iv) students applied for financial aid after 2011. Requirements (i) and (ii) ensure that each individual in our

[7] Some variation exists because the maximum covered amount depends on a reference tuition, which is set by the Ministry of Education based on estimates about the value-added of institutions and programs.

[8] Within the average (median) institution, the standard deviation in tuition fees between programs is 485 (464) thousand Chilean pesos. The standard deviation in tuition fees across institutions on the other hand is 880 thousand pesos. Using the average exchange rate of our last sample period (2015), this amounts to approximately $1,320.

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 that 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, 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 has only been 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.[9]

A final necessary requirement for our analysis is 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 A.3, a large subset of Chilean universities partially base their admission decisions on obtaining a minimum PSU result of 500 - the mean of the standardized test score distribution.[10] This leads to a situation, in which passing the threshold of 500 not only opens the possibility to obtain a grant but also significantly enlarges the choice sets in terms of university programs 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.

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.[11] Table 2 provides an overview over 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.

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

[10] 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 programs. See Neilson et al. (2022) for a discussion.

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

3 Reduced Form Analysis: Grants vs. Loans and Enrollment 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 normalized running variable and our targeted estimand as the standard sharp RD parameter:

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

Here Y_i can be either an indicator for enrollment in higher education or in a specific field, respectively (see below), and τ captures the change in the average enrollment 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.[12] Note that as in all RD studies, our results should be interpreted as valid for the population of individuals around the cut-off and not as average treatment effects for the full population.

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

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

The parameter of interest then is β_1, which quantifies potential discontinuous jumps around the normalized 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, Cattaneo and Farrell (2020). To gain precision in our estimation, 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

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

Table 2: Sample Summary Statistics

	Mean	S.D.	Min	Max	N
High School GPA	5.63	0.47	4	7	193,604
# Working Family Members	1.18	0.72	0	16	195,031
# Studying Family Members	0.10	0.33	0	7	195,031
Enrolled	0.73		0	1	195,031
Enrolled in STEM	0.26		0	1	195,031
Female	0.55		0	1	195,031
Single Mother HH	0.19		0	1	185,826
Academic Parents	0.37		0	1	182,959
Took Science Test	0.60		0	1	195,031
Municipal School	0.35		0	1	194,258
Subsidized School	0.59		0	1	194,258
Academic School	0.71		0	1	195,031
Income quintile $\times$ year:					
Quintile 1 x 2012	0.23		0	1	195,031
Quintile 2 x 2012	0.12		0	1	195,031
Quintile 3 x 2012	0.08		0	1	195,031
Quintile 2 x 2013	0.17		0	1	195,031
Quintile 3 x 2013	0.12		0	1	195,031
Quintile 2 x 2014	0.16		0	1	195,031
Quintile 3 x 2014	0.12		0	1	195,031
Region:					
Far North	0.05		0	1	195,031
Near North	0.06		0	1	195,031
Central	0.75		0	1	195,031
Near South	0.12		0	1	195,031
Far South	0.01		0	1	195,031

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 inludes Aysen, and the Magallanes and Chilean Antarctica. Reference category for Enrolled and Enrolled in STEM: non-enrollment or enrollment in any other major. Academic Parents is an indicator equal to one in case at least one parent has a university degree. Took Science Test is an indicator equal to one in case the student chose science as the voluntary component in the PSU test.

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.

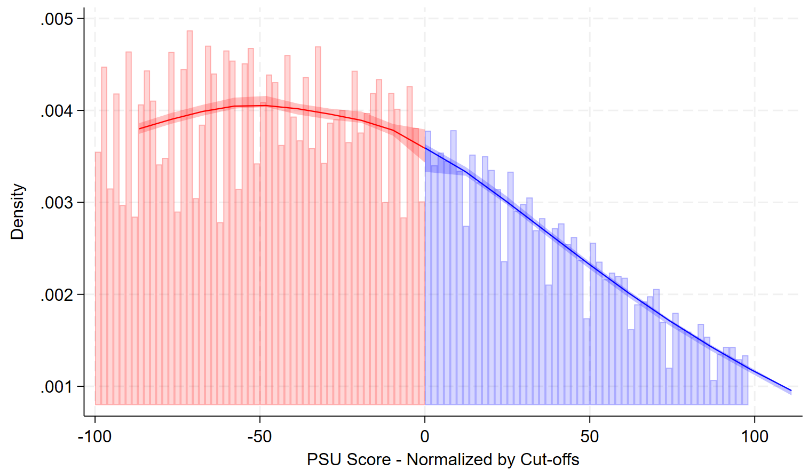
Identifying Assumptions. Before moving on to the empirical results, we want to briefly discuss the plausibility of the conditions under which β_1 identifies a causal effect. As is standard, the necessary identifying assumption for sharp RD models requires continuity in potential outcomes around the threshold. 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 nation-wide standardization 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 3 presents estimates of model (2) treating standard socio-demographic covariates as outcome variables. We find our sample balanced among all but two 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, Jansson and Ma (2020, 2021). We find no evidence for discontinuities in the density of test scores around the cut-off.

Given that our main identifying assumption is plausibly satisfied, β_1 identifies the causal effect of crossing the grant eligibility 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. Figure 2 on the other hand shows that, not surprisingly, 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 A1).[13] This implies that the setting we study allows us to focus our analysis on exogenous variation in the access to two different schemes of higher education financing.

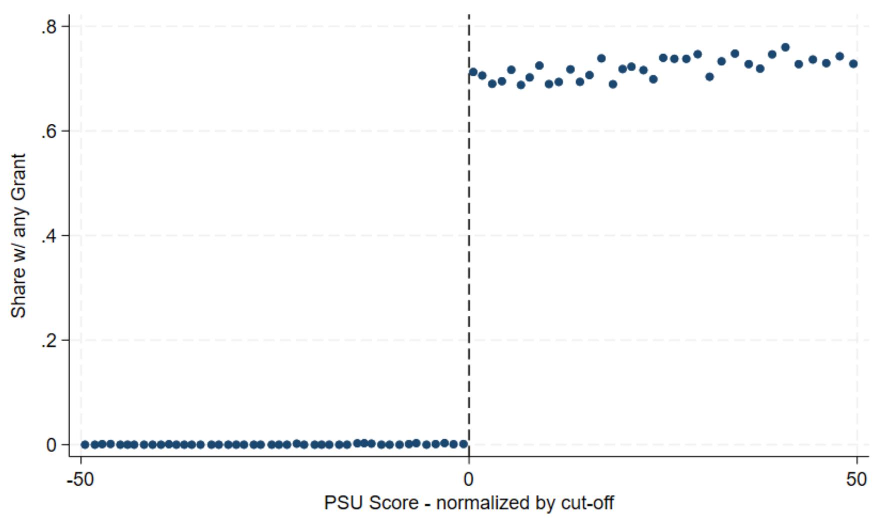
[13]Figure A2 displays the change in take-up at the cut-off separately for the two types of grants. In both cases demand increases discontinuously at the cut-off, but take up for the BG is increasing when moving further to the right of the threshold, while it is decreasing for the JGM. This is driven by the fact that the BG grant is more generous and applicable only to CRUCH universities, for which higher PSU test scores are required for admission.

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, Jansson and Ma (2020, 2021).

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 1.25 PSU point bins around the grant eligibility cut-off (normalized 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 enrollment, whereas we plot the unconditional probability of taking a grant.

Table 3: Covariate Balance around Grant Eligibility Cut-off

	Baseline Mean (β_0)	RD Estimate (β_1)	Standard Error ($\hat{\beta}_1$)
High School GPA	5.725	0.002	0.008
# Working Family Members	1.159	-0.001	0.011
# Studying Family Members	0.100	-0.004	0.005
Female	0.540	0.004	0.007
Single Mother HH	0.188	-0.004	0.004
Academic Parents	0.445	-0.015**	0.009
Took Science Test	0.667	0.002	0.009
Municipal School	0.271	-0.007	0.004
Subsidized School	0.673	-0.010**	0.004
Academic School	0.809	-0.006	0.006
Income quintile × year:			
Quintile 1 × 2012	0.175	0.004	0.015
Quintile 2 × 2012	0.118	-0.007	0.010
Quintile 3 × 2012	0.091	0.001	0.008
Quintile 2 × 2013	0.178	-0.002	0.019
Quintile 3 × 2013	0.127	-0.010	0.012
Quintile 2 × 2014	0.184	0.006	0.023
Quintile 3 × 2014	0.126	0.007	0.013
Region:			
Far North	0.051	0.000	0.004
Near North	0.065	-0.002	0.004
Central	0.740	0.002	0.008
Near South	0.127	-0.001	0.005
Far South	0.013	-0.001	0.005

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. $^{**}p < 0.05$, $^{*}p < 0.10$.

Outcomes of and Population of Interest. Our outcomes of interest are binary indicators for enrollment 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 the Basic Sciences. We combine the latter groups into one category, which we define as STEM.[14]

We pay particular attention to changes in enrollment in STEM. Majors in STEM are an interesting group to consider, since they are not only characterized by high monetary returns, but also by a higher earnings variance and a lower probability of degree completion. To see that consider data from *MiFuturo* (www.mifuturo.cl), a large publicly available data set provided by the

[14]This includes majors such as mathematics and statistics, chemistry, physics, the life sciences, computer science, engineering, and a variety of technology-related vocational degrees.

Chilean Ministry of Education. Since 2011, it allows prospective students to obtain information about average labor market earnings of past graduating cohorts at the institution by major level. It also contains information about the 10th, 25th, 50th, 75th, and 90th percentile of graduate earnings, one to five years after graduation, as well as dropout rates one and two years after starting to study. We use this information to summarize mean expected earnings, coefficients of variation, and dropout probabilities at the aggregated field level and display the results in Tables A1 and A2. Indeed STEM fields are those with the highest earning graduates on average and those where the fewest students persist with their studies after one and two years.

For each binary indicator, the reference group consists of the remaining college majors or non-enrollment. 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.[15]

When thinking about the external validity of our regression discontinuity exercise, note that comparing the observable socio-demographic characteristics of our full study sample (Table 2) to that of students at the grant eligibility cut-off (Table 3) reveals interesting similarities. 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 slightly more likely to have college educated parents and to have attended subsidized schools and schools with an academic track. While our population of interest – students at the grant eligibility cut-off – consequently is not a perfectly random sample of applicants to financial aid, the two groups are still fairly comparable in observable characteristics and our results are therefore likely to be informative for a more general population than the one we consider.

3.2 Average Treatment Effects

Focusing first on the average effect of grant eligibility on enrollment in STEM majors, we present point estimates in Table 4. As indicated by column (1), those prospective students that do marginally qualify for a grant are 2.9 percentage points more likely to enroll STEM related fields than those that would have to rely exclusively on student loans to finance their education. To put this into perspective, note that the enrollment rate in STEM fields for marginally ineligible students is approximately 25%. The RD estimate thus points towards an increase in enrollment of approximately 12.5%.

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

Table 4: Effect of Grants vs. Loans on Enrollment and STEM

	STEM (=1) (1)	Engineering (=1) (2)	Sciences (=1) (3)
RD Estimate	0.029***	0.023***	0.005**
	(0.007)	(0.007)	(0.002)
Baseline Mean	0.253	0.232	0.021
Bandwidth	41	44	46
Effective N	52,522	56,358	58,733

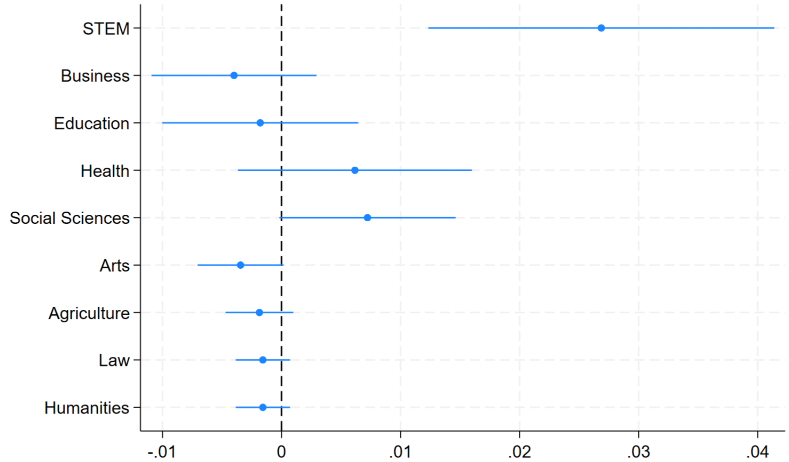
Note: ** $p < 0.05$, *** $p < 0.01$.
All dependent variables are binary indicators. Reference category for STEM, Engineering, and Sciences: non-enrollment or enrollment in any other major. The table presents estimates for β_1 in equation (2). All specifications are estimated using weighted local linear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

Columns (2) and (3) of Table 4 further differentiates 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, note that the baseline level of enrollment in the natural sciences is significantly lower, with only 2.1% of those marginally ineligible for grants enrolling in science programs, but 23.4% enrolling in engineering. Relative to these baseline numbers, the observed change is considerably larger in the natural sciences.

Moving beyond STEM degrees, we note that the results for the remaining eight aggregate fields of study are less pronounced. Figure 3 displays point estimates and confidence intervals using each of the fields separately as an outcome. We observe a slightly higher (lower) enrollment in social sciences (humanities) in response to gaining access to grants.[16] Interestingly, Hastings, Neilson and Zimmerman (2013) estimate STEM, health, and social science degrees to be those with the highest monetary returns in Chile, whereas the humanities are characterized 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 enrollment in lower return fields. This is at odds with findings for US universities (Rothstein and Rouse, 2011; Stater, 2011), where the opposite seems to be the case. However, we do observe, albeit measured too noisily to conclude they are different from zero, negative point estimates on law and business

[16]Note that baseline enrollment rates for marginally ineligible students differ widely across fields. Figure A3 re- scales the point estimates in Figure 3 to account for these baseline differences and illustrates that the effect sizes on enrollment in STEM, the Social Sciences, and the Humanities are comparable.

Figure 3: 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-enrollment or enrollment in any other field. Each specification includes the covariates outlined in Table 2.

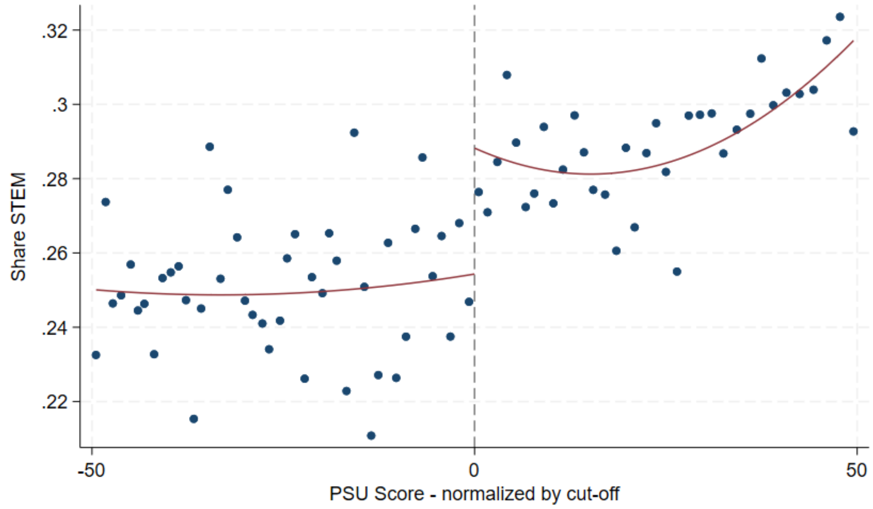
fields - two majors that do not qualify as low return fields. A simple story of financial aid altering a pecuniary vs. non-pecuniary trade-off is therefore not sufficient to rationalize our findings.

While our reduced form results suggest a rejection of the hypothesis that grants incentivize students to choose lower return fields, the correlation of returns and risk (labor market and study related) at the level of field of study motivates us to move beyond a pure regression-discontinuity approach. In section 4 below, we provide evidence for the mechanisms at play by highlighting which program characteristics interact with the two types of financial aid to drive students enrollment patterns.

Robustness and Auxiliary Analyses. In the analysis above, we use optimally chosen, data-driven, bandwidths (Calonico, Cattaneo and Farrell, 2020) to estimate our RD models. Figure 4, on the other hand, plots mean-enrollment rates in STEM fields for students in bins of 1.25 PSU test score points around the cut-off. While enrollment rates are quite volatile for those ineligible for grants, there is hardly any group of students above the threshold with enrollment rates below 26%. This presents some non-parametric evidence in favor of our main result. To corroborate Figure 4, we re-estimate our model for a series of different bandwidths ranging from 20 to 80 PSU points and show in Figure A4 that point estimates are fairly constant across vastly different bandwidths.[17]

[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

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



Note: The figure shows shares of students enrolled in STEM fields within 1.25 PSU point bins around the grant eligibility cut-off (normalized to zero across years and income quintiles).

As argued above, we do exclude individuals for which the relevant cut-off to gain eligibility for grants is a PSU score of 500. This is to rule out that our estimates pick up a treatment different from grant eligibility - namely, changes in students' choice sets produced by admission policies. An additional check to assess whether we estimate a genuine treatment effect or a mixture of different changes at the cut-off is to re-estimate our models on a population of students that took the test in order to apply for university, but that are not eligible for grants because their family income is too high (i.e., quintiles four and five of the distribution, see Table 1). In Figure A7 we present the results of this placebo exercise, which confirms our main findings in that we cannot identify any treatment effect for this ineligible population.

Besides affecting college major choices of students, we show in Table A4 that grant eligibility also has some implications for the extensive margin of students' choices.[18] We see an overall increase in enrollment in higher education (4% relative to the baseline mean) at the cut-off. This is particularly true for universities (as opposed to vocational higher education institutions), and, differentiating further within universities, for those that are part of the CRUCH network of traditional, more prestigious institutions.

The observation that grant eligibility both increases enrollment at universities and in STEM fields raises the question of whether the observed changes in field choices are driven by

admission policies in Chile.

[18]See Figures A5 and A6 for the non-parametric results at the extensive margin.

supply side considerations. If universities happened to be more specialized in STEM related fields than vocational institutions, we might misinterpret a desire for enrollment in more prestigious institutions with the choice of STEM. We think this alternative story is unlikely to be true, since 31.2% of all programs that are offered by universities can be classified as STEM, whereas the respective number is 31.7% for vocational institutions (see Table A7). Both institution types thus seem to have similar levels of specialization at the aggregated field measure we use. The picture changes somewhat, if we focus on CRUCH universities separately from other universities. For them, 40.7% of all programs are STEM related according to our classification. The higher share of STEM fields at CRUCH universities relative to vocational institutions is driven exclusively by the natural science, whose share at vocational institutions is essentially zero. If the alternative story of supply-side driven changes in enrollment in STEM were correct, we would expect our results to be driven mainly by enrollment in the natural sciences. While, as discussed above, we do see a stronger effect on the natural sciences relative to their baseline level of enrollment, the magnitude is far too small (0.5 percentage points increase) to explain the large increase in STEM enrollment that we observe at the aggregate (3 percentage points increase).

We conclude from this analysis that, while it is the case that students use grants to enroll in more prestigious universities, the composition of majors offered at these institutions is unlikely to drive the sorting patterns we observe with respect to enrollment in STEM fields. A direct impact of the type of financial aid on field choices through distinct field characteristics is the more plausible mechanism.

3.3 Heterogeneous Treatment Effects

We explore heterogeneity in the effect of financial aid along three dimensions: gender, parental education, and parental income. To do so, we re-estimate model (2) separately for each of our considered subgroups, 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.[19] For each group we choose optimal data-driven bandwidths (Calonico, Cattaneo and Farrell, 2020).

Table 5 presents the point estimates by subgroups and tests for difference in the effect sizes. Point estimates are smaller for female than for male students, for people whose parents have a university degree, and for students from relatively higher income families. Note that we

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

Table 5: Heterogeneity in the Effect of Grants on Enrollment 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		
	Second-Gen	First-Gen	Δ of Coefficients
RD_Estimate	0.025***	0.033***	0.008
	(0.009)	(0.010)	(0.013)
Baseline Mean	0.251	0.252	
Bandwidth	53	39	
Effective N	28,202	28,344	
	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-enrollment or enrollment 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, Cattaneo and Farrell (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

cannot reject the null hypothesis of equal effect sizes for male and female students. This result is particularly interesting given the vastly different baseline enrollment rates in STEM across gender. While only 13% of marginally ineligible female students enroll in STEM fields, almost 40% of male students do. Relative to these baseline figures, grant eligibility actually increases STEM enrollment more strongly for female than for male students. For female students the effect corresponds to a 15% change relative to baseline. We therefore find some mild evidence that substituting student loans with grants could shrink gender gaps in STEM enrollment, which has been a target of a series of former policy initiatives (see e.g., Cimpian, Kim and McDermott, 2020).[20]

[20]Tables A8 and A9 repeat the heterogeneity analysis splitting STEM into engineering and science majors. Doing

Contrary to the case of gender, baseline enrollment 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 enrollment rates are comparable. For both dimensions of heterogeneity, we do not find any evidence of differential effects. Students from relatively poorer and less educated families appear to react slightly more sensitively to become 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 of equal effects across groups.[21]

4 Mechanisms: The Interaction between Financial Aid and Program Characteristics

The RD analysis presented above reveals that, on average, access to grants increases enrollment rates in STEM degrees. This is in contrast with findings from the US, for which empirical evidence seems to suggest that more generous financial aid leads to an orientation towards careers with lower earnings (Rothstein and Rouse, 2011), at least initially (Hampole, 2022). At the same time STEM degrees are characterized by high dropout rates and a longer time to degree completion. 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 enrollment in narrowly defined programs (major $\times$ institution type) using a host of observable program 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 program characteristic, holding constant all other included observable program-level information. Before discussing the choice model and the empirical strategy, we first introduce the data on program characteristics we exploit for this analysis.

so reveals that female students are considerably more likely to use grants to enroll in science degrees, whereas male students adjust by choosing engineering more frequently.

[21] Table A10 in the appendix repeats the heterogeneity analysis for general enrollment in higher education. We do not find statistically significant group-differences in the response to changes in financial aid at the extensive margin along gender lines and with respect to parental education. For each considered subgroup, we find an increase in general enrollment. The largest difference in effect sizes is between students from the bottom income quintile (5.2 percentage points increase) and from quintiles two and three (2.8 percentage points). However, also in this case, our data is not informative enough to distinguish this difference from chance at conventional confidence values.

4.1 Data on Program Characteristics

Given the correlation between program characteristics such as labor market returns and dropout rates, a study of the mechanisms through which financial aid affects individual choices should preferably involve a narrow definition of university programs. Relying solely on the nine aggregate fields of study we used in the reduced form analysis so far, for instance, is not sufficient to create enough variation in labor market returns, while fixing other program characteristics. We circumvent this issue by relying on data from *MiFuturo*, which we introduced briefly already in section 3.2.

MiFuturo is part of a transparency initiative started in 2011 by the Chilean Ministry of Education, aimed at improving the quality of program choices of prospective students. On an easy to access and easy to navigate homepage (www.mifuturo.cl), anyone interested can retrieve program characteristics at the institution by major level.[22] The information used to characterize programs are realized outcomes of past graduating cohorts and include: labor 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 realized study duration, the share of female students, the share of students from subsidized and public schools, respectively, and the share of students passing their first year of study. Data on this is summarized in the so called *buscador estadísticas por carrera* (search engine for career statistics).

We retrieve data on 206 narrowly defined programs from the *buscador estadísticas por carrera* database. The underlying data stems from the universe of students entering the Chilean higher education system from 2000 onward. Note that while 206 programs are a higher level of aggregation than the precise student level program choice (e.g., University of Chile - Biology), they are defined narrowly enough to allow for the inclusion of all program characteristics for which we have data. To give an idea of how narrow we define choices, included alternatives in the choice model are for instance environmental chemistry at a university, or social work at a vocational institution. There are two shortcomings of the data provided by *MiFuturo*. First, it does not necessarily translate directly into individual-level subjective expectations about program-specific returns. However, given the easy accessibility to program-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. Second, the level of aggregation of programs is too high to include geographic information at the program-level. We can therefore not include city fixed effects

[22] See Figure A9 for an example involving mathematics and statistics at universities.

Table 6: Summary Statistics for Program Characteristics across Alternatives

	Mean	S.D.	Min	Max
Employed, year 1	0.765	0.152	0.226	0.991
Employed, year 2	0.820	0.129	0.331	1
Earnings, year 1 (100,000 Ch. Pesos)	5.693	2.804	2.268	23.498
Earnings Growth, year 1 to 5	1.442	0.185	0.923	2.108
Earnings Pct. 90/Pct. 50, year 5	1.916	0.335	1.207	3,762
Earnings Pct. 90/Pct. 10, year 5	4.026	1.086	1.830	8.580
Dropout	0.293	0.095	0.07	0.547
Excess Study Time (in Semesters)	3.215	1.761	0.824	10.48
Formal Study (in Semesters)	7.679	2.406	4	14.026
University	0.519		0	1
Business & Management	0.15		0	1
Agriculture	0.039		0	1
Arts & Architecture	0.063		0	1
STEM	0.437		0	1
Social Sciences	0.098		0	1
Law	0.019		0	1
Education	0.092		0	1
Humanities	0.024		0	1
Health	0.078		0	1

Note: the table presents summary statistics across 206 programs that we include as choice alternatives in the model. Dropout gives the average share of people not continuing their study in a given program after year 1, whereas Earnings Growth displays the ratio of the average earnings five years after graduation over average earnings one year after graduation.

or the distance between the location of a program and the home location of an individual.

Table 6 presents summary statistics on program characteristics across the 206 alternatives in our sample. We observe a large degree of variation across programs in almost every considered dimension. While for instance, in the *safest* program only 7% of students drop out on average after one year of study, this number rises up to 54.7% in the *riskiest* program. Similarly, average earnings one year after graduation range from 226,800 monthly Chilean pesos in the lowest earning program to 2.3 million in the highest. The by far largest share of included alternatives are programs that can broadly be characterized as STEM (43.7%), followed by business and management programs (15%). A slight majority of all alternatives are offered at universities, while the rest is offered at vocational higher education institutions.

4.2 Discrete Choice Model and Empirical Strategy

As highlighted throughout the paper, there are many (potentially complex and dynamic) ways in which financial aid and the payback structure of it might interact with individual college major choices. For the purpose of contrasting the role of the substantial set of program 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.

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 programs, defined as a combination of institution type (university, vocational) and major.[23] Each program is characterized 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, normalized by the relevant grant eligibility cut-off, and ϵ_{ij} an idiosyncratic program-specific taste shock. We allow for an interaction between characteristic $x_{j,k}$ and PSU_i^*. This implies that differences in PSU test results might lead to different evaluations of program characteristics, possibly in a way that is unrelated to financial aid. This is a reasonable assumption if higher PSU test results allow prospective students to access a larger set of programs with a different make-up in terms of observable characteristics. It also implies that by normalizing PSU_i using the grant eligibility cut-off, τ_k^g is informative for the utility contribution of program-characteristic k for members of group g at the cut-off (i.e., for $PSU_i^* = 0$). 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 $\_k$. At the same time, $\Delta_k \equiv \tau_k^{Grant} - \tau_k^{Loan}$ provides information about the differences in valuation between those that are marginally eligible for grants and those that are not, which is our comparison of interest.

[23]Note that non-enrollment in higher education is not in the choice set. While some students might choose not to enroll in higher education in the first place, there is no obvious counterfactual for some of the important characteristics that we consider in the model (e.g., dropout rates). We therefore condition our analysis on enrollment. Given the comparatively small effect of grant eligibility at the extensive margin (see Section 3.2), it is unlikely that our estimates are significantly affected by this restriction.

Estimation and Identification of Δ_k. As is standard in discrete choice modeling, we assume that ϵ_{ij} is i.i.d. type I extreme value, which together with the utility specification (3) implies that our set-up reduces to a classic conditional logit model, where the probability of individual *i* choosing any program *j* is:

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

We use this theoretical probability together with the program-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 3.2, we restrict our estimation to individuals within a narrow bandwidth around the grant eligibility cut-off and use weights following a triangular kernel-weighting. This has two main advantages. First, if the continuity assumptions underlying the regression-discontinuity analysis above are valid, applying the same logic to the discrete choice model implies that 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 programs is unproblematic, if the share of female students is continuous at the cut-off. In Section 3.1 we provide ample evidence in favor of this assumption.

Second, studying utility differences at the cut-off is helpful in identifying differences in the valuation of program characteristics, even if the levels of valuation for each group are not identified. It is unlikely the case that the set $\{x_{jk}\}_k$ fully captures the program characteristics driving individual choices, which implies τ_k^g and β_k^g are not identified by our approach.[24] However, the identifying assumption on $\Delta_k = \tau_k^{Grant} - \tau_k^{Loans}$ is much weaker and requires that the omitted variables biasing the estimation of τ_k^g are themselves not correlated with the grant eligibility cut-off. In this case, the bias cancels out by considering the difference in coefficients between the two groups. While the identifying assumption on our parameter of interest Δ_k is milder than the one on τ_k^g, it is still fundamentally untestable. 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.

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

4.3 Results

Table 7 displays estimates for the difference in valuation of various program characteristics between grant and loan holders (i.e., for Δ_k). The underlying sample corresponds to the sub-populations of students in our RD sample (see section 3.1) within 15, 20, and 25 PSU point windows around the grant eligibility cut-off. Each model additionally adjusts for the remaining program characteristics outlined in Table 6, as well as the share of female students, the share of students coming from public and subsidized schools, respectively, and tuition fees.

Table 7: Difference in Valuation of Characteristics across Aid Types: Δ_k

	(1)	(2)	(3)
Excess Study Time	0.05	0.055*	0.054**
	(0.035)	(0.03)	(0.027)
Share Dropout	1.83**	1.269*	0.907
	(0.824)	(0.714)	(0.638)
Earnings, year 1	-0.035	-0.023	-0.018
	(0.033)	(0.028)	(0.024)
Earnings Growth, year 1 to 5	0.364	0.407	0.339
	(0.358)	(0.309)	(0.276)
Earnings Pct.90/Pct.10	-0.047	-0.036	-0.023
	(0.081)	(0.070)	(0.062)
Share Employed	-0.014	-0.619	-0.767
	(2.000)	(1.715)	(1.525)
N	15,114	20,298	25,293
Bandwidth	15	20	25

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The table presents estimates for the difference in utility parameters between those eligible for grants, $PSU_i^* \geq 0$, and those that are not, $PSU_i^* < 0$. *Excess Study Time* is the time until graduation of an average graduate minus the formal time to graduation as specified in the study regulations. *Share Dropout* is the share of students dropping out after one year of study. *Share Employed* is the share of graduates in employment within two years of graduation. Each model additionally adjusts for field of study: STEM, Humanities, Health, Law, Arts, Social Sciences, Agriculture, Education, Business and Management, the share of students from public and subsidized schools, the share of female students, tuition fees, institution type (university / vocational), the earnings pct. 90/pct. 50 ratio, the share of employed graduates within one year after graduation, the formal time to graduation according to study regulations, and the interaction of each characteristic with individuals' PSU score. The number of programs in the choice set of each individual is 206. Standard errors in parentheses.

We do not find evidence for a different valuation of labor market outcomes between the two groups. Students with access to grants are not more likely than their peers with student loans to value high earnings growth, high employment probabilities after graduation, or high initial earnings. There is also no difference in the distaste for uncertainty in labor market earnings, as measured by the ratio of earnings at the 90th to the 10th percentile.[25] While these last results might sound surprising at first, bear in mind that the repayment of student loans in Chile is income-contingent. The counterfactual scenario to grants therefore already is a type of financial aid that provides some insurance against labor market risks (Britton, van der Erve and Higgins, 2019; Lochner and Monge-Naranjo, 2016).

In contrast to the results on labor-market characteristics, we do find that programs that are associated with higher dropout rates and a larger share of students exceeding the formal time to degree completion are valued relatively more favorably by grant recipients than by student loan holders. While the estimates are more sensitive to bandwidth choices than the regression-discontinuity results presented above, this is true for each considered bandwidth.[26] Importantly, it is also true conditional on various other program characteristics and dummies for the more aggregate fields of studies we used in our reduced form analysis. The variation we consider is consequently within these more aggregate degrees. In fact, we demonstrate in Table A12 in the Appendix that, conditional on finer program characteristics, aggregate measures of field of study are not evaluated differently across aid types. Looking at more aggregated measures of field choices alone can therefore miss an important part of the picture.

Our analysis takes the notion that college majors are mixed bags of correlated characteristics seriously and provides suggestive evidence that among the considered program characteristics, it is study-related uncertainty that is driving the results we are picking up in our regression-discontinuity analysis. The presented evidence suggests that students with access to grants are more likely to enroll in STEM degrees, even though there is a higher risk of taking longer to graduate or drop out. In contrast to the student loan system Chile has in place, grants provide insurance against the financial uncertainty of not knowing when and if starting a program will lead to a degree. A natural follow-up question then is what the effects of this insurance mechanism on the selection and the behavioral response of marginally enrolling students are. We address this concern in the following section.

[25]To reiterate the discussion in the section above: this statement applies to the *difference* in valuation but the level of valuation for each group is unlikely to be identified by our approach. For completeness, Table A11 in the Appendix presents the group-level estimates. As one might suspect, both groups of students value program characteristics such as employment probabilities or earnings growth in a positive, and dropout rates and earnings uncertainty in a negative way.

[26]Note that relative to the regression-discontinuity analysis, here we gain precision by making distributional assumptions on the taste shocks of prospective students. This allows us to focus on much narrower bandwidths around the grant eligibility cut-off, which is helpful in terms of our identifying assumptions.

5 Realized Graduation and Time To Completion

The analysis of the mechanisms behind enrollment decisions supports the notion that student financing their education through grants take more study-related risks when choosing a major. This may spur concerns about the negative impact of increased risk-taking on graduation rates and the time taken to complete a program. Students who, in an alternative scenario, would have opted for an easier choice could encounter even more challenges in successfully finishing their studies.[27] At the same time, grants may enhance graduation by alleviating financial stress and the need to work during students' college years. The theoretical direction of the effect thus is not obvious and the empirical evidence is mixed (see e.g., Angrist, Autor and Pallais, 2022; Matsuda and Mazur, 2022). In this section, we study the impact of grant eligibility on dropout and time to degree completion but do not attempt to distinguish between these different explanations.

To investigate whether marginal students are more or less likely to drop out or require additional study time, we track students that enrolled in the year of their first PSU attempt.[28] As the available information on graduation extends until 2022, and we encompass data up to cohort 2014, we will define students as "graduated" if they obtained an undergraduate degree within eight years after their initial PSU test.[29] Similarly, we will measure years to completion for the sample of students that graduated within this time span.

Results Table 8 presents regression-discontinuity estimates based on specification (2). That is, 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 for the population of individuals enrolled just after completing high-school, the 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 programs (see column 2). For our sample,

[27]While this argument relates to adverse selection, another reason why grant recipients might perform worse than loan takers is moral hazard. In fact, previous empirical work by Garibaldi et al. (2012) and Beneito, Boscá and Ferri (2018) shows that students with lower tuition fees tend to prolong their study time in college. However, unless the degree of moral hazard brought about by more generous financial aid is different across various majors, this channel cannot explain why students incentivized by grants to take more challenging fields perform worse than they would have if enrolled in another program.

[28]Hence, we condition on enrollment. While enrollment status technically is affected by grant eligibility itself, the effect of aid at the extensive margin is of small magnitude, as we show above. At the same time, the enrollment effect is large enough to mechanically increase graduation rates among grant holders, irrespective of the channels we are interested in. For this reason, we exclude non-enrolled PSU test takers. In A10 and A11, we present results on graduation unconditional on enrollment.

[29]In the Appendix we perform the same analysis but focusing only on cohorts 2012 and 2013, for which we can exploit information up to 9 years after the first PSU attempt. The results, shown in A13, are essentially unchanged.

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

	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)
Baseline Mean	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, Cattaneo and Farrell (2020). Standard errors are clustered at the PSU test score level and reported in parentheses. Effective N summarizes the number of observations with non-zero weight given the chosen bandwidth. Baseline Mean 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 enrollment in columns 3 to 6.

we consequently find no evidence for 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 that enrolled in STEM and is marginally eligible for a grant spends an additional year in college. While this might be indicative of adverse behavioral responses of students to grant eligibility, note that an alternative explanation is that students with grants might be more likely to enroll in programs that require more time to be completed also according to their formal study requirements – in section 3.2 we for instance show that grant eligibility increases enrollment in universities as opposed to vocational institutions, where degrees are typically of shorter length. In columns (4) and (6) of Table 8, we repeat the analysis, conditional on the number of semesters formally required to finish the respective program chosen by each student. By doing so, we can assess the influence of eligibility status on student behavior, independent of program duration. The coefficients are halved relative to a specification that doesn't adjust for program length and are not statistically distinguishable from zero.

Collectively, our results suggest a limited role for adverse selection or behavioral responses of grant holders. This is in line with Matsuda and Mazur (2022), who calibrate a heterogeneous agent model to an income-contingent loan reform in the U.S. and who find that the reform induced only little moral hazard and adverse selection. While it is true that grants allow students to choose degrees with higher overall dropout rates and expected time until degree completion, marginally eligible students are not different in observable performance indicators than their peers that enrolled in these degrees despite having to rely on student loans.

6 Concluding Remarks

Using large administrative records from Chile, we find that students that are marginally eligible for grants make vastly different college major choices than students that have to rely on loans. They are more likely to enroll in STEM related fields and, more generally, in fields with higher average earnings but also with higher dropout rates. Given the institutional setting in Chile, being marginally eligible corresponds to being among the average students in terms of academic preparedness, since the necessary requirement for eligibility is scoring 525 or 550 points in the standardized 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, 2015), our results are therefore informative for policies targeted at a broader set of students.

With the help of a discrete choice model over heterogeneous higher education programs, we illustrate that one way to rationalize our reduced form results is by noticing that an access to grants as opposed to loans encourages students to try their luck in high return, yet hard to finish, programs. These programs are more likely to fall in the aggregate field of study that is STEM. 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. From a methodological point of view, our approach allows us to characterize the interaction between financial aid and specific program characteristics, while holding other program features constant. Given the correlation between different program characteristics, this allows us to provide a more comprehensive picture of the mechanism through which financial aid alters students' choices.

When interpreting our results in the light of the financial aid environment of other countries, it is important to keep in mind that students in Chile make their enrollment 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 for the results should take this into account. Nonetheless our results clearly 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.

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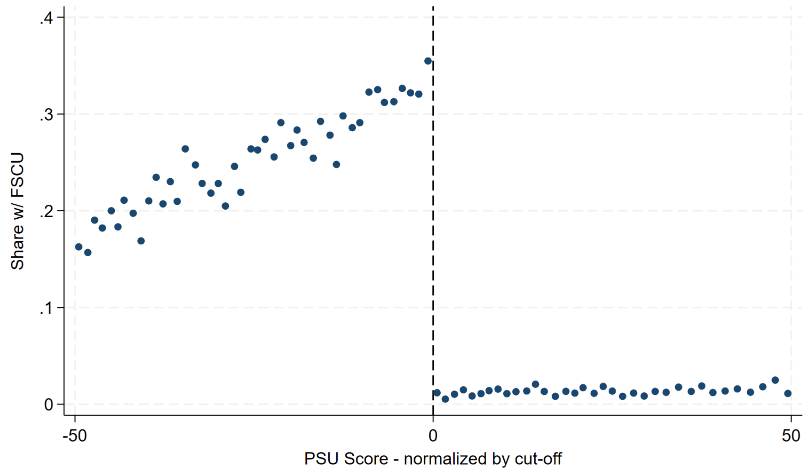
Appendix

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

Adriano De Falco and Yannick Reichlin

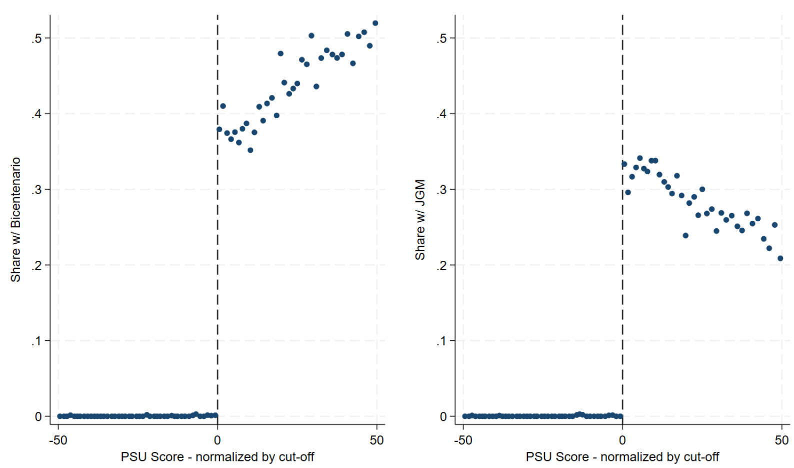
A.1 Additional Figures

Figure A1: Take up of FSCU loan around the eligibility cut-off



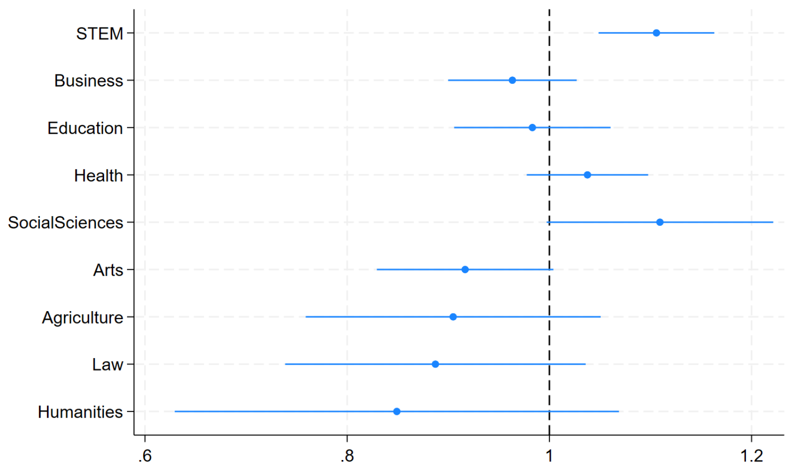
Note: The figure shows the average take-up of FSCU student loans in 1.25 PSU point bins around the grant eligibility cut-off (normalized to zero across years and income quintiles).

Figure A2: Take up of Bicentennial Grant and JGM around the eligibility cut-off



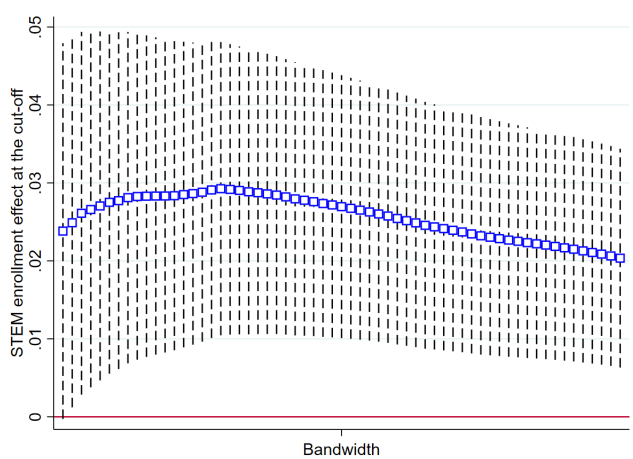
Note: The figure shows the average take-up of the Bicentennial Grant (left) and the JGM Grant (right) in 1.25 PSU test score bins around the grant eligibility cut-off (normalized to zero across years and income quintiles).

Figure A3: Effect of Grants vs. Loans Relative to Baseline Enrollment



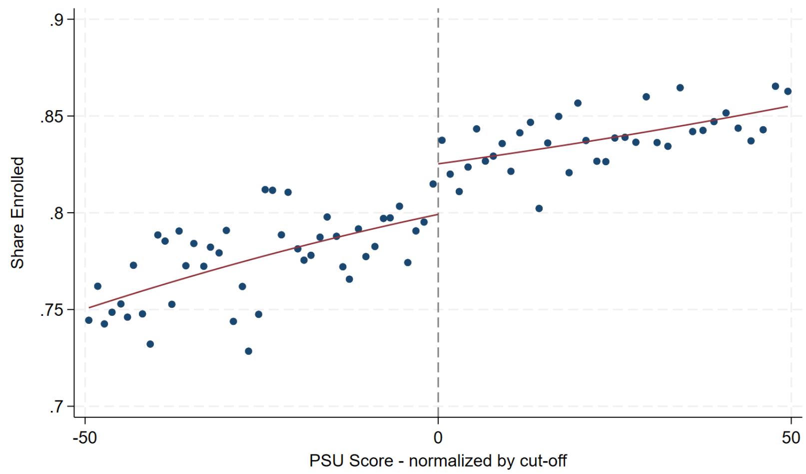
Note: The figure shows the ratio of the shares of marginally eligible students choosing each respective option to the corresponding share of marginally ineligible students. See also Figure 3 for the point estimates on percentage point changes at the cut-off that are used to construct the ratios here.

Figure A4: Effect of grant eligibility on STEM at the cut-off as function of bandwidth



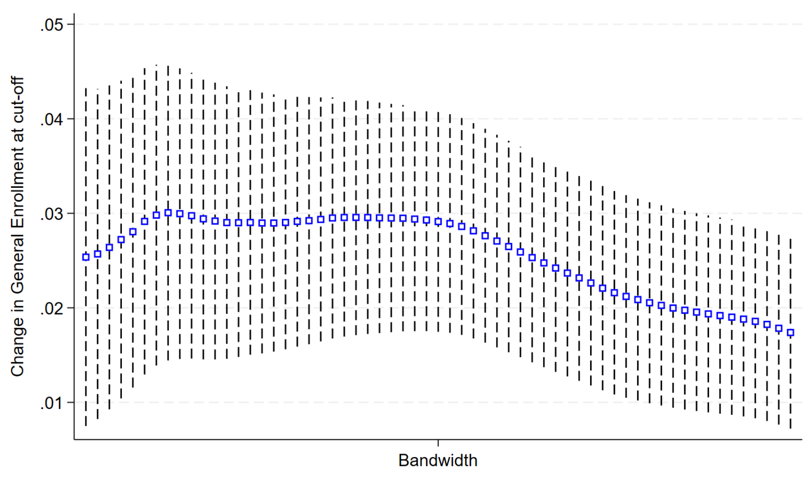
Note: The figure shows estimates and 95% confidence intervals for β_1 in specification (2) for different value of the bandwidth. The bandwidths values range from 20 to 80.

Figure A5: General enrollment around the cut-off



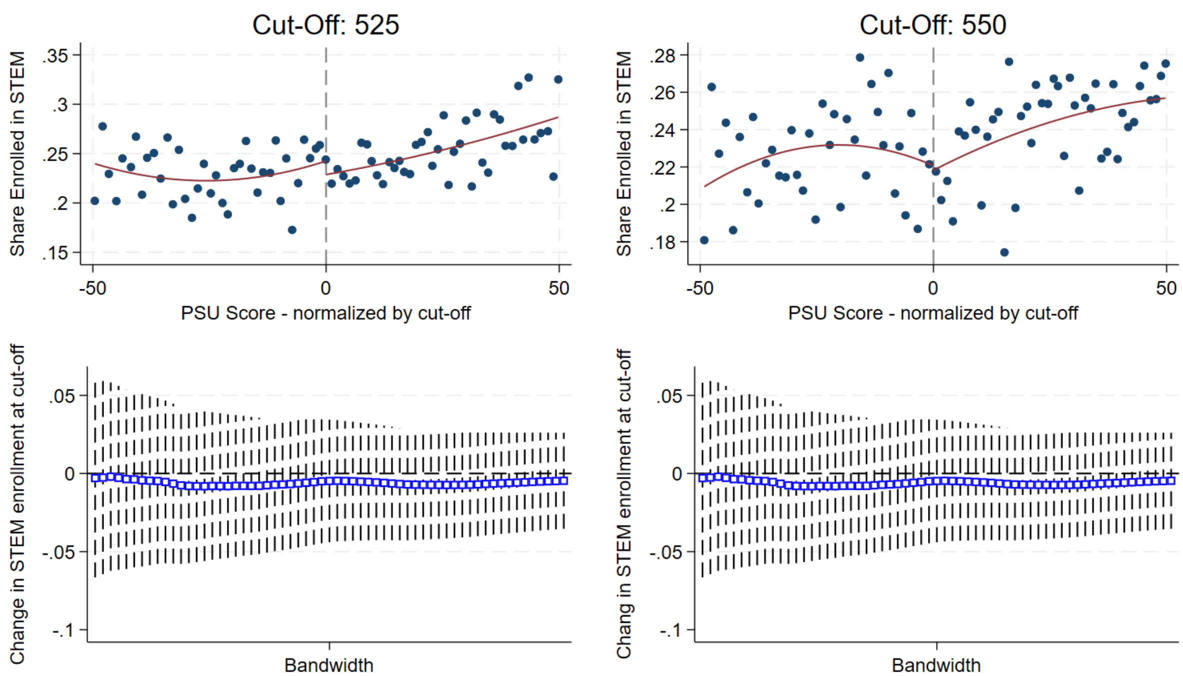
Note: The figure shows shares of students enrolled in any higher education institution in 1.25 PSU point bins around the grant eligibility cut-off (normalized to zero across years and income quintiles).

Figure A6: Effect of grant eligibility on general enrollment as a function of bandwidth



Note: The figure shows estimates and 95% confidence intervals for β_1 in specification (2), using different bandwidths. The bandwidth values range from 20 to 80.

Figure A7: Placebo Test for enrollment in STEM



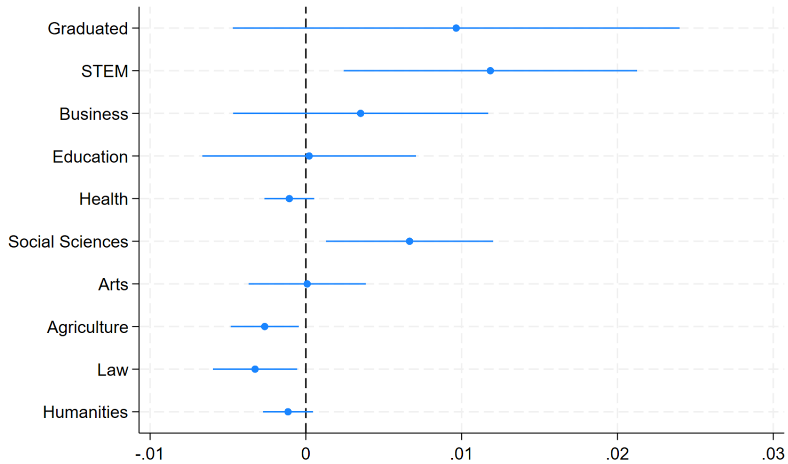
Note: The figure shows placebo tests for the effect on enrollment in STEM. The estimation sample consists of students of the the cohorts 2013 and 2014 that applied for financial aid but that are ineligible for grants because of a too high background family income (fourth and fifth quintile). The cut-offs were normalized 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 enrollment rates in STEM fields in 1.25 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) for different value of the bandwidth. The bandwidths values range from 20 to 80.

Figure A8: Screenshot of mifuturo.cl

Figure A9: Screenshot of mifuturo.cl

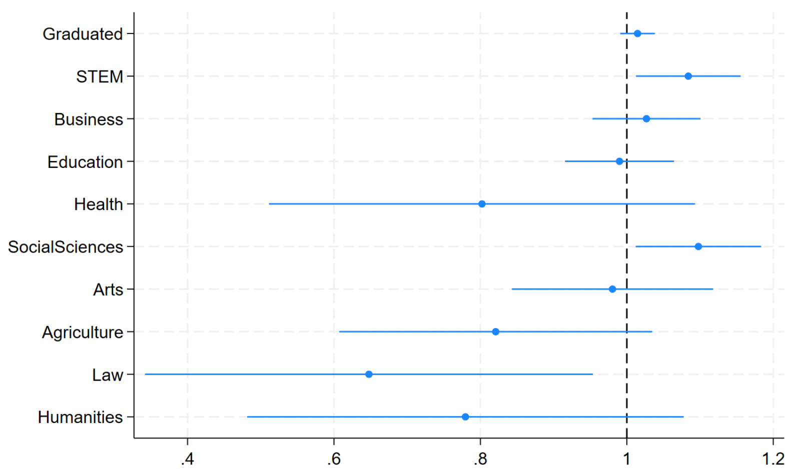
Note: The figure displays a screenshot of mifuturo.cl and illustrates how interested students can retrieve program-level characteristics. In this case the evolution of average wages over the first five years for past graduates of the majors (up), the number of graduates and number of semester needed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

Figure A10: Effect of grant eligibility graduation 8 years after first attempt on PSU



Note: The figure shows estimates and 95% confidence intervals for β_1 in specification (2). The outcome is a binary variable taking value 1 if the individual graduated in a specific field eight years after the first attempt on the PSU. Each specification includes covariates outlined in Table 2 and year by family income quintile fixed effects.

Figure A11: Effect of Grants vs Loans on Graduation Relative to Baseline



Note: he figure shows the ratio of the shares of marginally eligible students graduating eight years after the first PSU attempt in each respective option to the corresponding share of marginally ineligible students. See also Figure A10 for the point estimates on percentage point changes at the cut-off that are used to construct the ratios here.

A.2 Additional Tables

Table A1: Earnings Information by Field of Study and Institution Type

	Universities		IP		CFT	
	Mean	$\frac{SD}{Mean}$	*Mean*	$\frac{SD}{Mean}$	*Mean*	$\frac{SD}{Mean}$
Business	10.03	0.24	7.58	0.23	6.42	0.19
Arts	7.19	0.19	5.48	0.19	5.04	0.15
Humanities	5.56	0.19	6.98	0.45		
Law	10.77	0.25	5.96	0.27	5.96	0.13
Social Sciences	7.34	0.20	6.90	0.17	6.03	0.22
STEM	11.51	0.27	7.61	0.23	6.96	0.22
Agriculture	7.71	0.23	5.77	0.24	5.22	0.17
Health	8.72	0.18	4.90	0.13	5.19	0.15
Education	6.54	0.14	4.70	0.13	4.19	0.12

Monthly earnings in 100,000 Chilean Pesos (approx. $125). Standard deviation imputed using empirical mean and 90th percentile of earnings, assuming a log-normal distribution. Data from mifuturo.cl.

Table A2: Dropout Probabilities by Field of Study

	Pr(Dropout After Year 1)	*Pr(Dropout After Year 2)*
Business	0.266	0.359
Arts	0.252	0.350
Humanities	0.264	0.328
Law	0.228	0.305
Social Sciences	0.225	0.290
STEM	0.283	0.373
Agriculture	0.227	0.290
Health	0.203	0.226
Education	0.201	0.241

Dropout probabilities by field after 1 and 2 years of study respectively. Data from mifuturo.cl.

Table A3: Effect of Grants vs. Loans on Enrollment in STEM in Different Institution Types

	Enrolled STEM in...		
	CRUCH	Private Uni	Vocational
RD_Estimate	0.020***	0.007**	0.001
	(0.005)	(0.003)	(0.004)
Baseline Mean	0.140	0.043	0.070
Bandwidth	50	50	50
Effective N	62,668	62,668	62,668

Note: ** $p < 0.05$, *** $p < 0.01$.
All dependent variables are binary indicators. Reference category: non-enrollment in STEM or enrollment in STEM in respective other types of institutions. The table presents estimates for β_1 in equation (2). All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are fixed to 50 PSU points to keep samples constant across specifications.

Table A4: Effect of Grants vs. Loans on Enrollment in Different Institution Types

	Enrolled in...			
	Any Institution	CRUCH	Private Uni	Vocational
RD_Estimate	0.032***	0.029***	0.009	-0.005
	(0.006)	(0.007)	(0.008)	(0.006)
Baseline Mean	0.797	0.357	0.295	0.146
Bandwidth	50	50	50	50
Effective N	62,668	62,668	62,668	62,668

Note: ** $p < 0.05$, *** $p < 0.01$.
All dependent variables are binary indicators. Reference category: non-enrollment or enrollment in respective other types of institutions. The table presents estimates for β_1 in equation (2). All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are fixed to 50 PSU points to keep samples constant across specifications.

Table A5: Effect of Grants vs. Loans on Enrollment and STEM: Split Sample Period

	2008 - 2011		Full Sample	
	Enrolled	STEM	Enrolled	STEM
RD_Estimate	0.014**	0.004	0.022***	0.012***
	(0.006)	(0.006)	(0.005)	(0.004)
Bandwidth	36	65	32	49
Effective N	74,383	127,659	108,633	161,725

Note: ** $p < 0.05$, *** $p < 0.01$.
All dependent variables are binary indicators. Reference category for STEM: non-enrollment or enrollment in any other major. The table presents estimates for β_1 in equation (2), 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, Cattaneo and Farrell (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Table A6: Shares of Programs per Field in Different Institutions

	Universities	**Vocational**	**CRUCH**	**Private Univ.**
Total Number	13,889	7,409	7,830	6,060
Share (%):				
Business/Management	8.9	26.6	8	10.1
Agriculture	3.1	3.5	3.2	10.15
Arts/Architecture	7.5	9.5	5.3	10.4
STEM:	30,1	31.8	40,8	18.2
Engineering	25.3	31.0	33.0	16.3
Natural Sciences	4.8	0.8	7.8	1.9
Social Sciences	11.4	5.6	8.5	15.2
Law	2.7	2.3	1.9	3.8
Education	19.9	8.6	19.6	20.4
Humanities	2.5	1.4	2.4	2.5
Health	13.8	10.8	11.6	16.5

Note: The Table displays shares of each field among all programs offered by the respective type of institutions. Programs are selected, if at least one enrolled student is a recent high school graduate, PSU test taker, and applied for financial aid. Data for the years 2008 to 2015. The number of programs per year is fairly stable, and so is the distribution of fields, conditional on year and type of institution.

Table A7: Effect of Grants vs. Loans: Non-STEM Fields

	Business & Management	Education	Health	Social Sciences
RD_Estimate	-0.006	0.000	0.008	0.008*
	(0.004)	(0.005)	(0.006)	(0.004)
Baseline Mean	0.109	0.106	0.164	0.066
Bandwidth	56	66	47	58
Effective N	70,125	81,231	59,758	72,555
	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	0.042	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-enrollment or enrollment in any other major. The table presents estimates for β_1 in equation (2). All specifications are estimated using weighted local linear regressions and include the covariates outlined in Table 2. Bandwidths are chosen optimally according to Calonico, Cattaneo and Farrell (2020). Standard errors are clustered at the PSU test score level and reported in parentheses.

Table A8: Heterogeneity in the Effect of Grants on Enrollment 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		
	Second-Gen	First-Gen	Δ of Coefficients
RD_Estimate	0.017*	0.029***	0.012
	(0.01)	(0.01)	(0.014)
Baseline Mean	0.23	0.23	
Bandwidth	56	43	
Effective N	29,608	31,130	

	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-enrollment or enrollment 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. Standard errors are clustered at the PSU test score level and reported in parentheses.

Table A9: Heterogeneity in the Effect of Grants on Enrollment 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		
	Second-Gen	First-Gen	Δ of Coefficients
RD_Estimate	0.008*	0.003	-0.005
	(0.004)	(0.003)	(0.005)
Baseline Mean	0.02	0.022	
Bandwidth	52	49	
Effective N	27,916	35,323	
	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-enrollment or enrollment 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. Standard errors are clustered at the PSU test score level and reported in parentheses.

Table A10: Heterogeneity in the Effect of Grants on General Enrollment

		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	
	Second-Gen	First-Gen	Δ of Coefficients
RD_Estimate	0.037***	0.031***	-0.006
	(0.013)	(0.009)	(0.016)
Baseline Mean	0.797	0.798	
Bandwidth	39	34	
Effective N	21,601	24,957	
		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 A11: Valuation of Program Characteristics, τ_k^g, by Aid Type

	Loan	Grant	Loan	Grant	Loan	Grant
	(1)	(2)	(3)	(4)	(5)	(6)
Excess Study Time	0.018	0.068***	0.013	0.068***	0.013	0.067***
	(0.025)	(0.024)	(0.021)	(0.021)	(0.019)	(0.019)
Share Dropout	-5.521***	-3.691***	-5.269***	-4.000***	-5.016***	-4.109***
	(0.586)	(0.579)	(0.505)	(0.505)	(0.450)	(0.452)
Earnings, year 1	-0.029	-0.064***	-0.027	-0.050***	-0.022	-0.040**
	(0.024)	(0.022)	(0.021)	(0.019)	(0.018)	(0.016)
Earnings Growth, year 1 to 5	0.528**	0.892***	0.555**	0.962***	0.637***	0.976***
	(0.261)	(0.245)	(0.222)	(0.215)	(0.196)	(0.194)
Earnings Pct.90/Pct.10	-0.090	-0.137***	-0.089*	-0.125***	-0.085*	-0.108***
	(0.062)	(0.052)	(0.053)	(0.045)	(0.047)	(0.040)
Share Employed	1.164	1.150	1.466	0.847	1.556	0.789
	(1.444)	(1.384)	(1.217)	(1.209)	(1.068)	(1.088)
Bandwidth	15		20		25	
N	7,597	7,517	10,408	9,890	13,090	12,203

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The table presents estimates for the utility parameters of grant and loan recipients, i.e., $PSU_i^* \geq 0$ and $PSU_i^* < 0$, respectively, at the cut-off. τ_k^g in model 3. *Excess Study Time* is the time until graduation of an average graduate minus the formal time to graduation as specified in the study regulations. *Share Dropout* is the share of students dropping out after one year of study. *Share Employed* is the share of graduates in employment within two years of graduation. Each model additionally adjusts for field of study: STEM, Humanities, Health, Law, Arts, Social Sciences, Agriculture, Education, Business and Management, the share of students from public and subsidized schools, the share of female students, tuition fees, institution type (university / vocational), the earnings pct. 90/pct. 50 ratio, the share of employed graduates within one year after graduation, the formal time to graduation according to study regulations, and the interaction of each characteristic with individuals' PSU score. The number of programs in the choice set of each individual is 206. Standard errors in parentheses.

Table A12: Difference in Valuation of Aggregate Fields of Study across Aid Types: Δ_k

	(1)	(2)	(3)
STEM	0.12	0.172	0.185
	(0.194)	(0.168)	(0.15)
Business & Management	0.121	0.161	0.165
	(0.213)	(0.184)	(0.164)
Agriculture	-0.126	-0.073	-0.111
	(0.294)	(0.255)	(0.227)
Arts & Architecture	-0.16	-0.026	-0.051
	(0.311)	(0.268)	(0.237)
Humanities	-0.345	-0.382	-0.348
	(0.435)	(0.356)	(0.307)
Social Sciences	0.173	0.173	0.16
	(0.184)	(0.157)	(0.139)
Law	-0.228	-0.251	-0.249
	(0.315)	(0.272)	(0.242)
Education	0.185	0.21	0.203
	(0.199)	(0.171)	(0.153)
N	15,114	20,298	25,293
Bandwidth	15	20	25

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The table presents estimates for the difference in utility parameters between those eligible for grants, $PSU_i^* \geq 0$, and those that are not, $PSU_i^* < 0$. Reference field of study: Health. Each model additionally the share of students from public and subsidized schools, the share of female students, tuition fees, the earnings pct. 90/pct. 50 ratio, the share of employed graduates within one year after graduation, the formal time to graduation according to study regulations, the variables included in Table 7, and the interaction of each characteristic with individuals' PSU score. The number of programs in the choice set of each individual is 206. Standard errors in parentheses.

Table A13: Effect of Grants vs. Loans on Graduation Conditional on Enrollment - By Year 9

	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	0.019*	0.011	0.081	0.038	0.110	0.054
	(0.011)	(0.016)	(0.053)	(0.040)	(0.088)	(0.072)
Baseline Mean	0.669	0.514	6.146	6.146	6.052	6.052
Bandwidth	73	64	39	48	81	79
Effective N	48,353	14,115	18,679	22,666	8,975	8,851
# 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, Cattaneo and Farrell (2020). Standard errors are clustered at the PSU test score level and reported in parentheses. Effective N summarizes the number of observations with non-zero weight given the chosen bandwidth. Baseline Mean 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 9 years after enrollment in columns 3 to 6.

A.3 Choice Set Changes Around Grant Eligibility Cut-Off

In this 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 argument boils down to the fact that a subset of Chilean universities, including all CRUCH institutions and few additional private universities, participate in a centralized admission system, which partially relies on PSU scores for admission and matches students and programs (institution $\times$ major combinations) following a Deferred Acceptance algorithm.[30] 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 program 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

[30] See Table A14 for an overview over the number of programs participating in the central admission system and Larroucau and Rios (2020) for a detailed discussion of the algorithmic implementation of admission in Chile.

components of science or history. The relative weights for the PS are program specific.[31] Second, programs can require students to fulfill minimum requirements, in terms of the unweighted math-language average PSU score and the PS. In Figure A12, we plot the histogram of program-specific minimum requirements for each year of our analysis. As we can see, while only a subset use minimum requirements on the PS, every program imposes a minimum PSU requirements.[32] 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 case of competitive programs, yet do so in less demanded programs.

Using administrative data on decision weights used by each program and information about admitted students, we determine realized admission thresholds for each program. By definition, they correspond to the score of the last admitted student.[33] With this information we construct hypothetical choice sets for each student in our sample, taking into account both realized thresholds and minimum requirements. Figure A15 plots the average number of available programs 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.[34] 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 enrollment decisions. However, students who are marginally eligible for a grant see the composition of fields in their choice sets changing. Similarly to Figure A15, in Figure A16 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 programs discontinuously decreases at 500, at the expense of an increase in the share of education programs. It is reasonable to argue 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.

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

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

[33] As discussed, realized thresholds might differ from minimum requirements in competitive programs.

[34] 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.

Table A14: Shares of programs per field participating in the centralized system

	2008	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*
Total Number	940	938	960	976	1319	1374	1398	1413
Share (%):								
Business/Management	7.1	6.9	7.1	7.3	8.2	8.4	8.1	8.2
Agriculture	3.4	3.4	3.6	3	2.58	2.5	2.2	2.4
Arts/Architecture	5.3	5.4	5.3	4.8	5.8	5.7	5.7	5.8
STEM	39.9	38	39.9	39.5	34.5	34.6	34.1	33.4
Social Sciences	8.8	9.1	8.8	8.7	10	10.1	10.6	10.8
Law	2	2	2	2	2.6	2.5	2.6	2.5
Education	19.7	21	21.1	20.8	18.6	18.1	18.1	18.6
Humanities	2.2	2.4	2.2	2.3	2.9	2.8	2.4	2.4
Health	11.3	11.4	11.5	11.6	14.6	15.1	16.1	16.1

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

Figure A12: Distribution of minimum requirements over the years

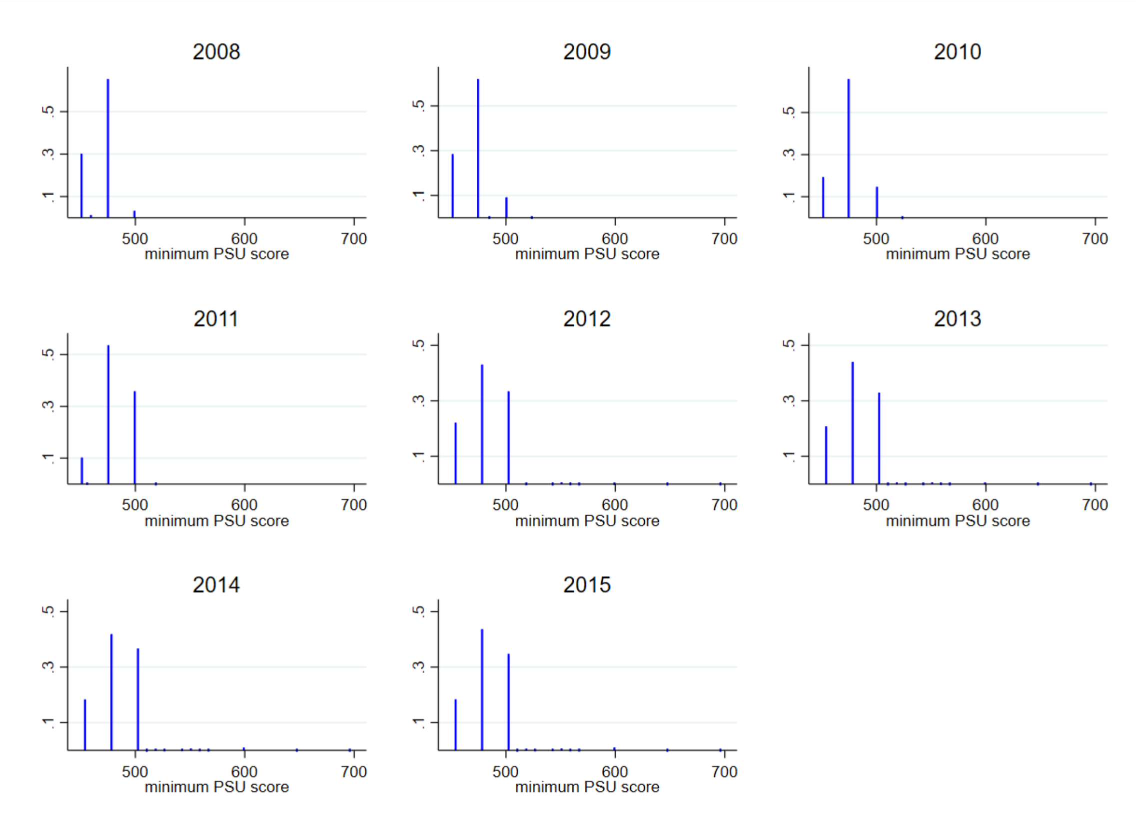


Figure A13: Density Minimum PSU Score.

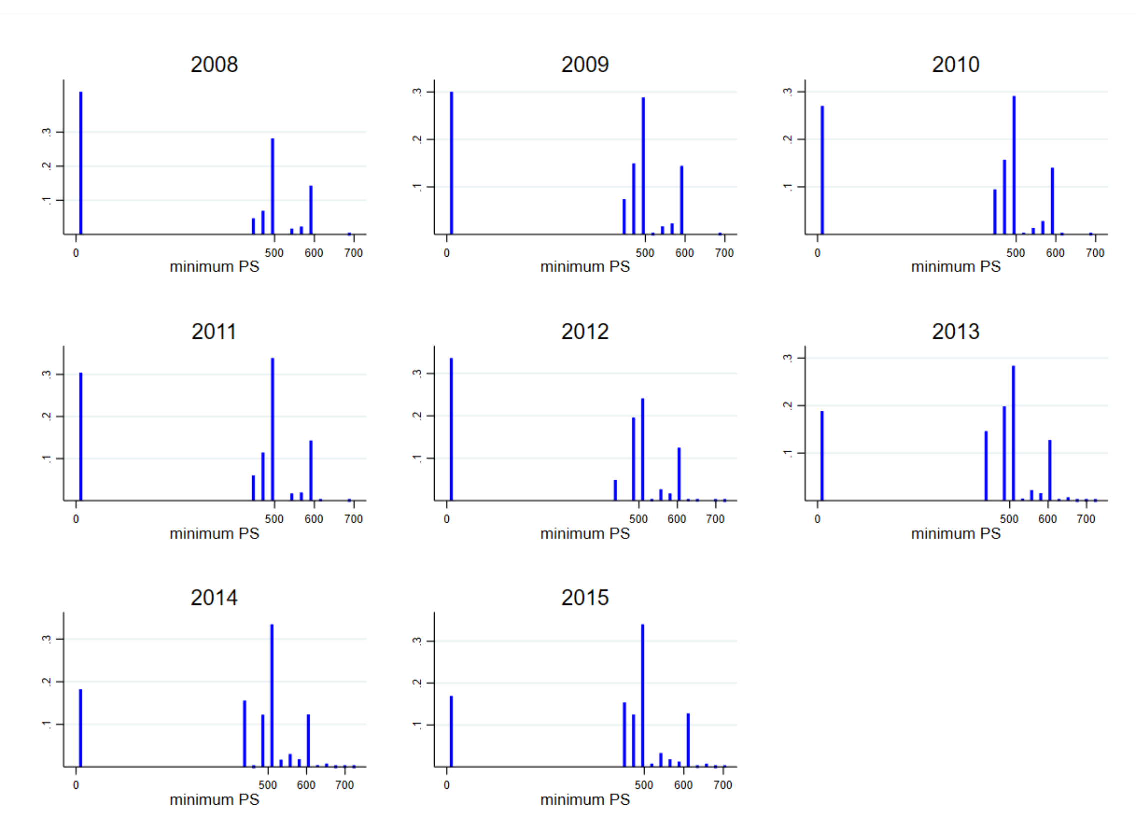
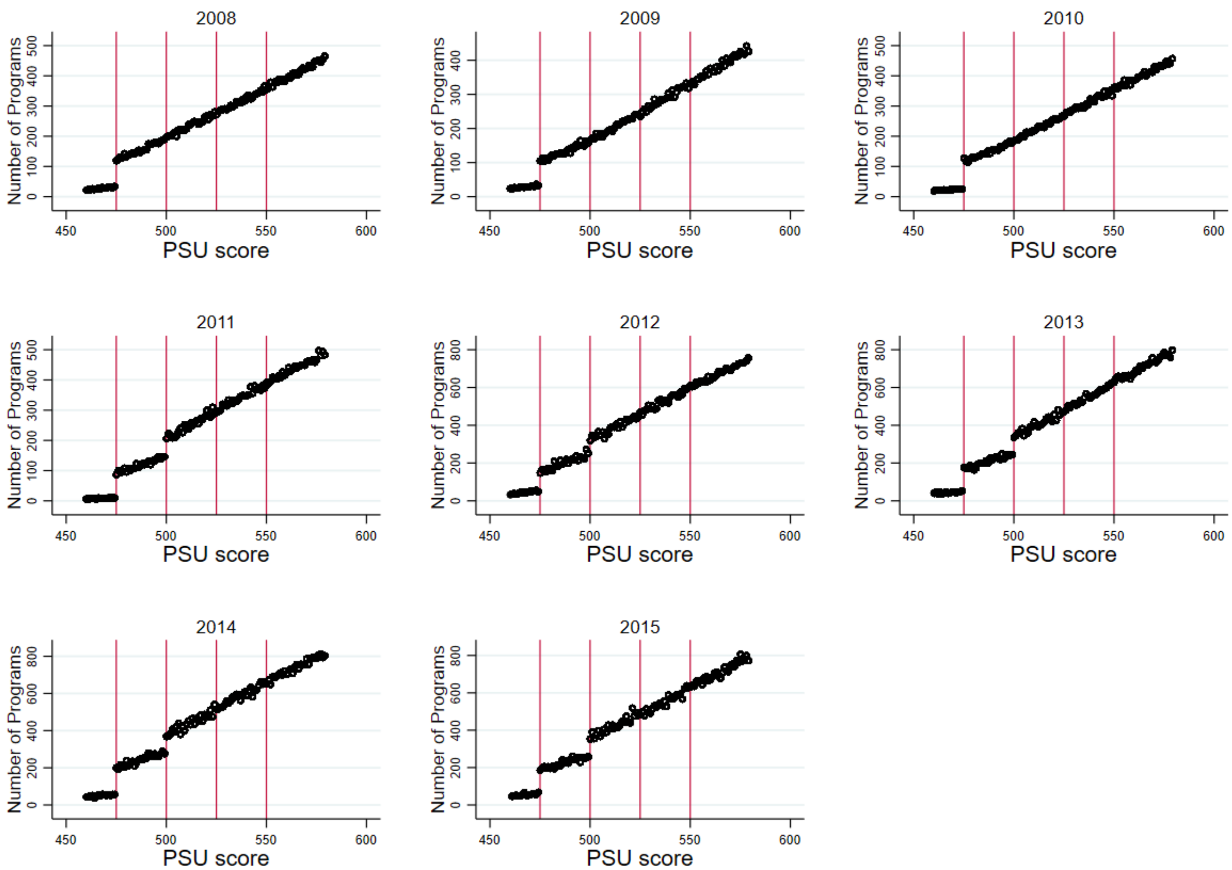


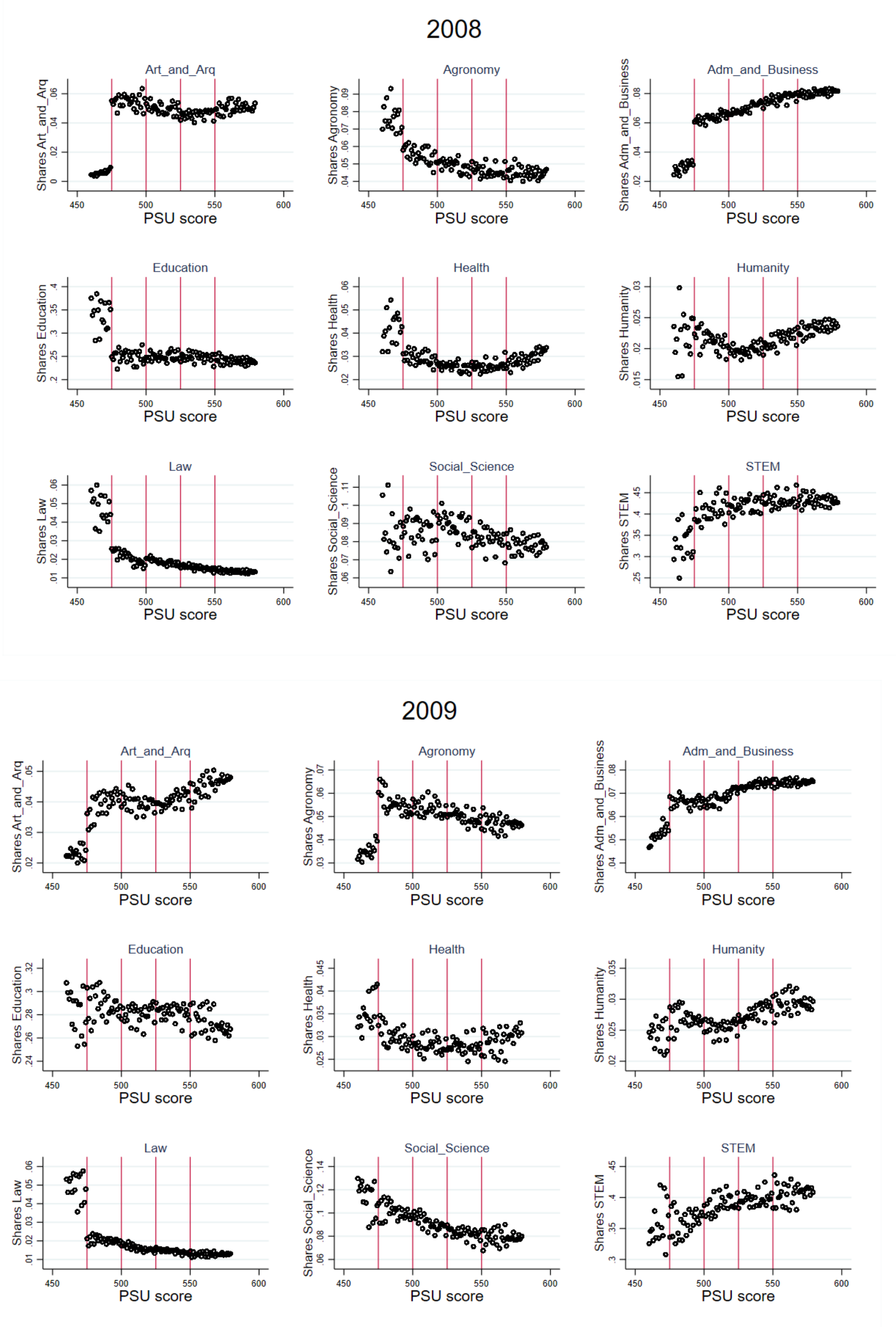
Figure A14: Density minimum PS

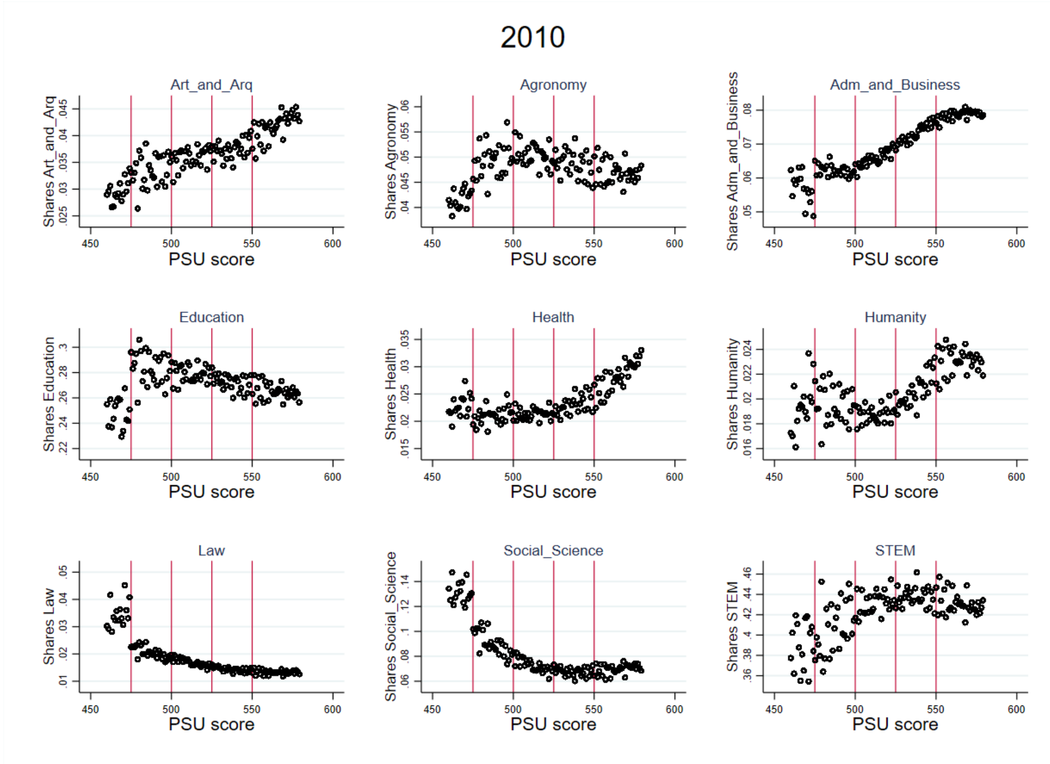
Figure A15: Number of centralized programs in the choice set as a function of PSU

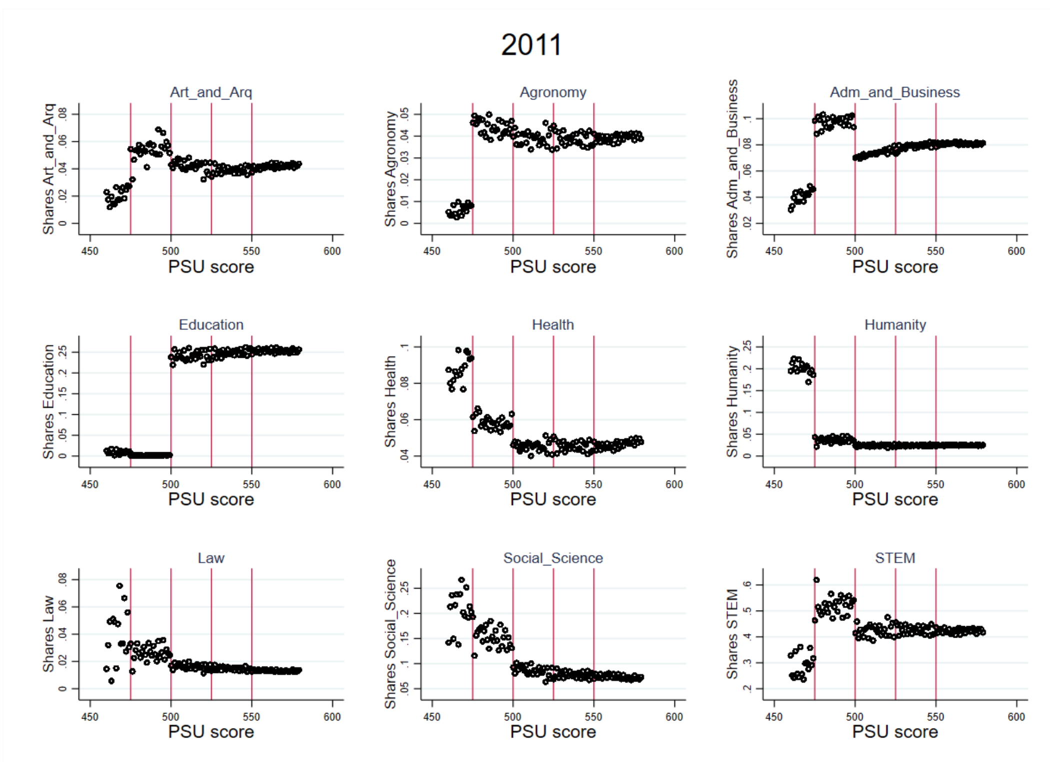


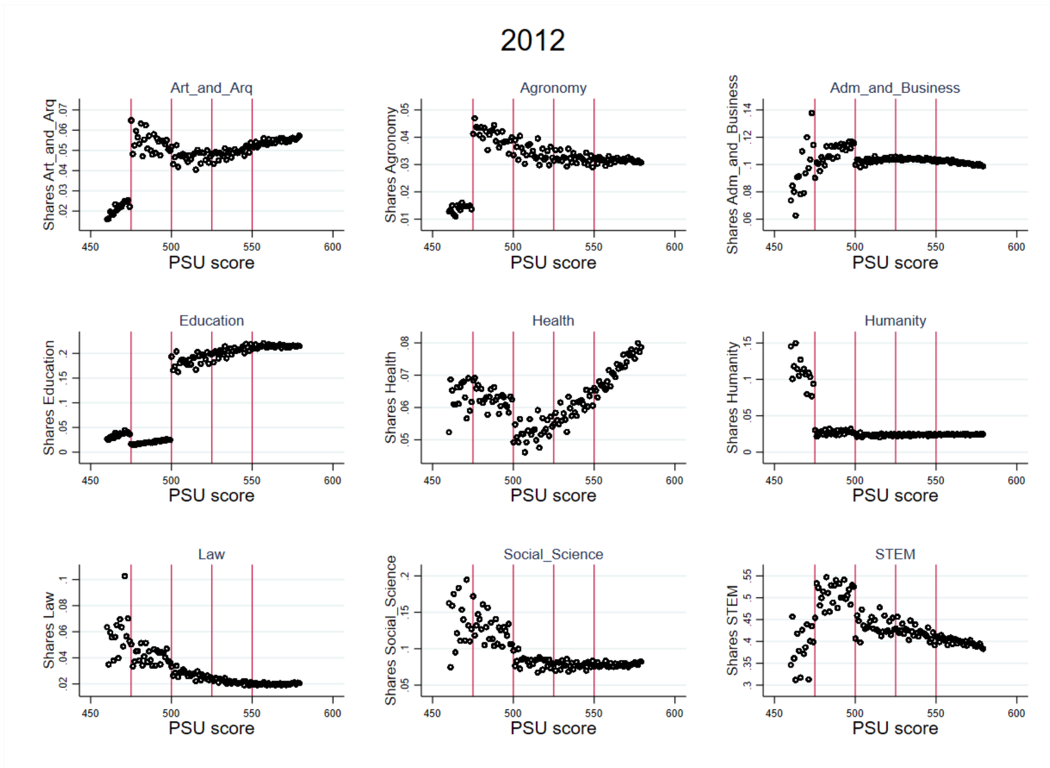
Note: The figures show the average number of available programs in students' choice sets as a function of PSU scores – PSU bins correspond to one point. The red lines refer to PSU scores of 475, 500, 525, and 550. The first threshold corresponds to eligibility for student loans. The last three are used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

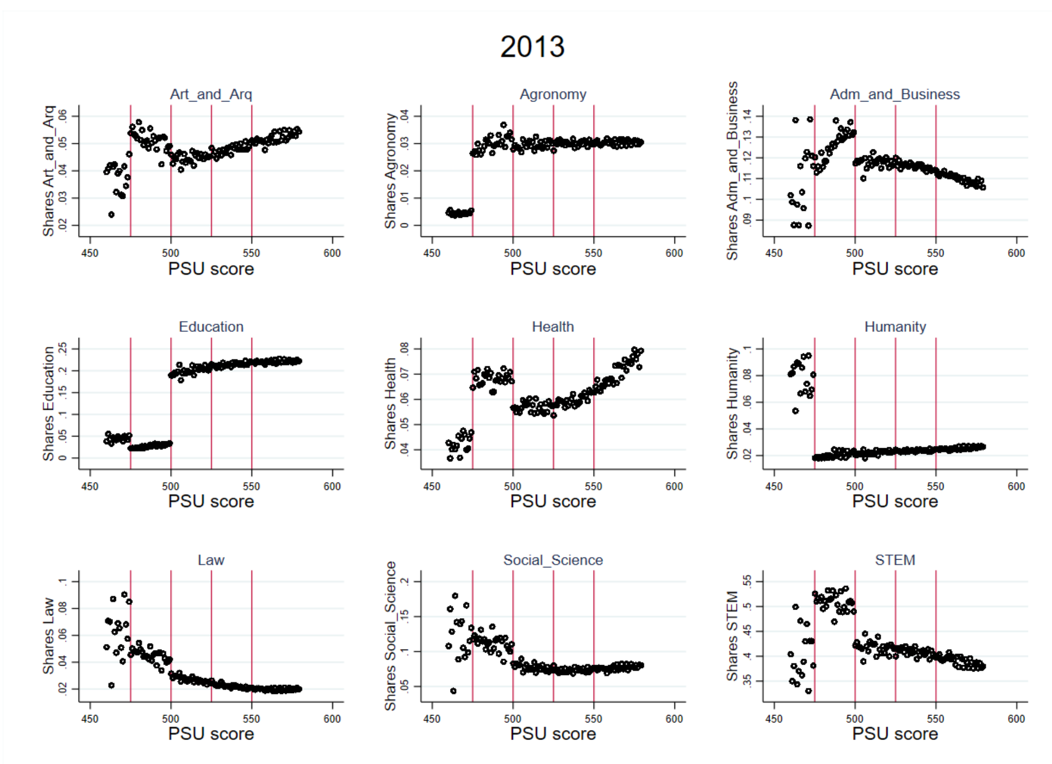
Figure A16: Shares of fields in the choice set as a function of the PSU score

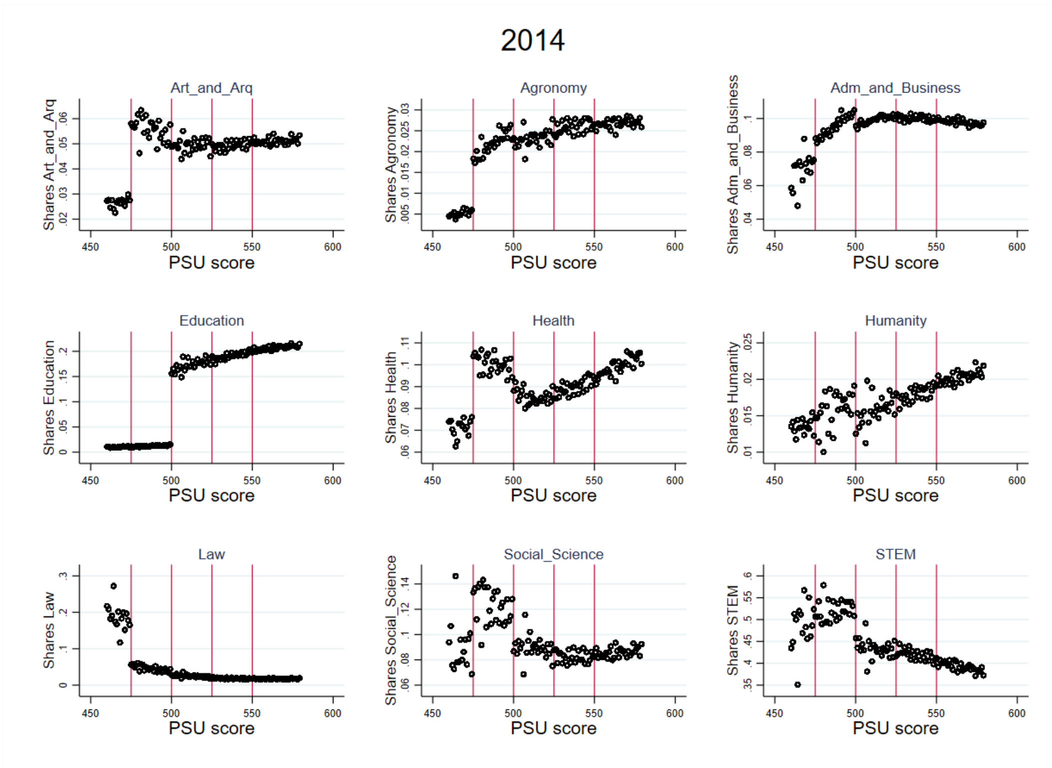


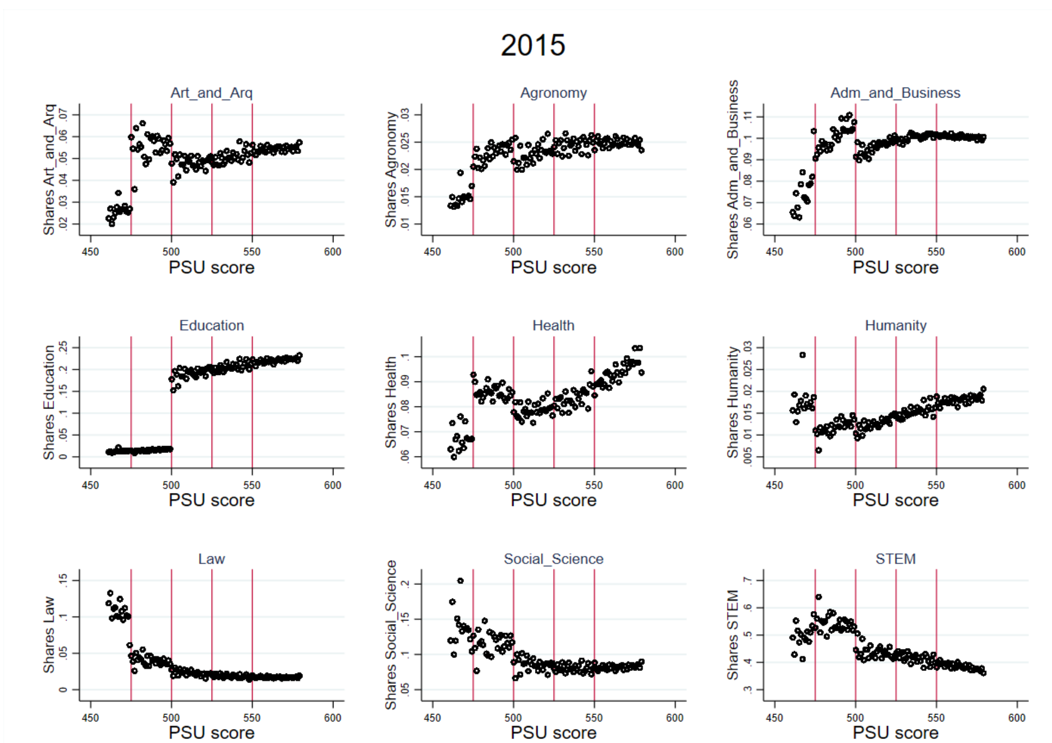

2010
Art_and_Arq
Shares Art_and_Arq
Agronomy
Shares Agronomy
Adm_and_Business
Shares Adm_and_Business
Education
Shares Education
Health
Shares Health
Humanity
Shares Humanity
Law
Shares Law
Social_Science
Shares Social_Science
STEM
Shares STEM
PSU score


2011
Art_and_Arq
Shares Art_and_Arq
Agronomy
Shares Agronomy
Adm_and_Business
Shares Adm_and_Business
Education
Shares Education
Health
Shares Health
Humanity
Shares Humanity
Law
Shares Law
Social_Science
Shares Social_Science
STEM
Shares STEM
PSU score


2012
Art_and_Arq
Agronomy
Adm_and_Business
Education
Health
Humanity
Law
Social_Science
STEM
Shares Art_and_Arq
Shares Agronomy
Shares Adm_and_Business
Shares Education
Shares Health
Shares Humanity
Shares Law
Shares Social_Science
Shares STEM
PSU score


2013
Art_and_Arq
Agronomy
Adm_and_Business
Education
Health
Humanity
Law
Social_Science
STEM
Shares Art_and_Arq
Shares Agronomy
Shares Adm_and_Business
Shares Education
Shares Health
Shares Humanity
Shares Law
Shares Social_Science
Shares STEM
PSU score





Note: The figure shows the average shares of the nine fields of study among available programs 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).