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Does Free Tuition Help or Hinder the Poor?

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ABSTRACT

DOES FREE TUITION HELP OR HINDER THE POOR?

By

ALFREDO MARTIN CASTRO

August, 2021

Committee Chair: Dr. Daniel Kreisman

Major Department: Economics

This dissertation consists of two chapters that study a free tuition policy in Chile. This is a politically charged issue on which there is still little evidence, which makes it a difficult but especially important policy to study. In 2016, Chile waived tuition for the poorest 50% of the population. In the first year of implementation, this policy covered mostly academic programs. In the second year, it was extended to technical education. This stepwise implementation offers an interesting perspective for studying the self-selection of vulnerable students in technical or professional careers.

In the first chapter, I exploit the arbitrary cut that this policy uses to estimate the effect of free tuition on the type of program low-income student choose. Using a Regression Discontinuity Design and a Difference-in-Difference approach, I show that the policy increased college enrollment for eligible students by around seven percentage points in total. This increase was driven mainly by high ability, low-income students, who enrolled in larger numbers and did so in higher quality institutions. Results suggest that despite a generous loan program in Chile, the removal of tuition for low-income students led to meaningful changes in college accessibility.

In the second chapter, I present the potential effect of this policy on the mismatching of vulnerable students. Through a detailed descriptive analysis, I show that access to higher education in Chile, especially to selective programs, is closely related to student income. The differential in student performance cannot fully explain this gap, suggesting that there are spaces to democratize access to higher education further.

As a whole, this thesis shows that low-income, high-performance students face economic constraints that prevent them from entering selective and high-return programs. This problem exists even in the absence of restrictions on access to credit, as shown in this case.

Does Free Tuition Help or Hinder the Poor?

By

Alfredo Martin Castro

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY

2021

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2021

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Table of Contents

List of Tables

List of Figures

Introduction

Unequal access to higher education is a problem that worries experts, politicians, and citizens alike. Accentuated by the increasing cost of college and the rise in student debt that this has entailed, this inequality reflects access to higher education and the type of programs to which people of different socioeconomic backgrounds choose. Low-income students tend not to enroll in college. Among those who enroll, the majority do so in technical programs, which tend to be shorter, less expensive, and with lower economic returns. How much of these decisions are due to economic constraints? It is an empirical question that still needs to be answered, which has significant public policy implications.

In this context, governments have different options to improve access to higher education for low-income students. Among these, free tuition is trending to the front of the political debate as countries, such as Chile, are moving in that direction, while others, such as England, have moved away from it. A significant group of politicians and economists argue that the free tuition would benefit more students of wealthier backgrounds, who would end up displacing more vulnerable students towards less selective, low-return programs. As they are better prepared for college selection tests, wealthier students have an academic advantage over low-income students, giving them a greater chance of benefiting from free tuition. This, added to how expensive this policy is, imposes excessive fiscal pressure for a policy that would end up being regressive.

On the other hand, high levels of debt and the economic uncertainty that many families face impose an excessive burden that diverts students from opting for careers with higher economic returns, which are usually more expensive and difficult. This causes a mismatch between students and the quality of the programs they access, where many high-achieving students end up enrolling in less selective programs. Those who defend free tuition do so from a normative perspective, understanding the right to education as a fundamental right where each student should access college according to their abilities and not their socioeconomic status. Despite the importance and controversy of free tuition, there are still no evaluations regarding its effect on access to higher education for low-income students.

In this dissertation, I study the first years of a free tuition policy in Chile that affected the poorest 50% of the population. This policy was implemented in two stages, only covering academic programs in the first year and then expanding it to technical programs in the second, which gives a unique perspective to the study. Focusing on differences by income level and high school performance, I present a detailed description of who benefits from free tuition and the type of programs students choose. At the same time, I study the causal effect of eliminating tuition on low-income students' decisions to attend academic or technical programs and their access to high-quality programs.

From an economic theory perspective, eliminating the cost of higher education can have different effects, both in the decision to enroll and in the type of programs that students choose. On the one hand, by reducing the cost of higher education, the expected return required to invest in education is now lower. Students with lower expected returns would be induced to enroll in college. On the other hand, since free tuition eliminates some of the risks of enrolling in college, we can expect high-achieving, low-income students to enroll in more expensive, higher-return programs. If students are risk-averse, low-income students will be less likely to pursue riskier programs than their wealthier peers, even when they have the same expected return. This is known in economics as Decreasing Absolute Risk Aversion. As the risk decreases, this difference between high- and low-income students should dissipate.

Finally, free tuition can also harm the most impoverished students. As more affluent students choose to enter free programs, poorer students may be displaced to less selective programs or simply out of college.

In the first chapter, I exploit the arbitrary cut that this policy uses to estimate the effect of free tuition on the type of program chosen by low-income students. Using a Regression Discontinuity Design and a Difference-in-Difference approach, I show that the policy increased college enrollment for eligible students by around seven percentage points in total. This increase was driven mainly by high ability, low-income students enrolled in larger numbers and enrolled in higher quality institutions. Results suggest that despite a generous loan program in Chile, the removal of tuition for low-income students led to meaningful changes in college accessibility.

In the second chapter, I present the potential effect of this policy on the mismatching of vulnerable students. Through a detailed descriptive analysis, I show that access to higher education in Chile and more selective programs is closely related to student income. The differential in student performance cannot fully explain this gap, suggesting that there are spaces to democratize access to higher education further.

As a whole, this thesis shows that low-income, high-performance students face economic constraints that prevent them from entering selective and high-return programs. This problem exists even in the absence of restrictions on access to credit, as shown in this case.

Chapter 1

The Causal Effect of Free Tuition on Low-income Students' Access to Higher Education

1.1 Introduction

Unequal access to college is a notable concern in research and policy. In the United States, for example, college affordability is a key policy concern among researchers, families, and politicians alike[1]. In Chile, rising student debt triggered massive protests demanding free tuition in 2012. In South Africa, students blocked access to different college campuses to protest tuition increases in 2015. As the cost of college and student debt continues to grow, governments and policymakers often face multiple options to improve access for low-income students. Among these, free tuition is trending to the front of the political discourse. The Democratic presidential nominee in the United States, Joe Biden, signaled that his administration would waive tuition at two-year colleges. And, while some countries, such as England, have moved away from free tuition, others, such as Chile, recently adopted this approach. Despite the significance of these decisions, there is still little evidence on how a free-tuition policy affects low-income students' decisions to attend college and the type of college they choose.

In this paper, I estimate the impact of a massive change to college pricing in Chile, resulting from a policy that waived tuition for the poorest half of the population. The policy was implemented in two steps, with four-year tuition prices going to zero in the first year and technical college tuition going to zero in the second, adding a unique perspective to the study. Focusing on differences in income and skill levels, I study how eliminating tuition affects students' enrollment in technical or academic programs and how the policy affected access to top-ranked programs for low-income students. Results can shed light on the degree to which students are financially constrained in attending (high quality) college, despite the universal availability of loans.

There are many ways how removing tuition may affect students' decisions, not only in whether to enroll in college but also in the type of program they choose. First, as the cost of education is

[1] https://www.pewresearch.org/fact-tank/2020/02/21/democrats-overwhelmingly-favor-free-college-tuition-while-republicans-are-divided-by-age-education/

now lower, students with lower expected returns may be induced to enroll in college. Those who would have gone to a technical program may now choose academic programs, which are generally more expensive and difficult. Second, as free-tuition policies eliminate some risk in the investment decision, for example, taking loans, low-income, high-achieving students may be induced to enroll in a higher return, more expensive program. On the other hand, as higher-income students, who are generally better prepared for college admission tests, decide to enroll in free institutions, they may push low-income students out of college or into lower-quality programs. The potential effects of free tuition at these different margins represent relevant policy questions regarding distributional effects that should be considered when evaluating inequalities in access to higher education.

The literature on financial aid has found mixed effects on college enrollment for low-income students. While need-based and place-based policies tend to benefit lower-income students (Linsenmeier, Rosen, and Rouse (2006); Alon (2011))[2]. The vast and growing literature on financial aid in the United States (see Page and Scott-Clayton (2016) for a review) contrasts with the scarce evidence in developing countries. Despite the implementation of free-tuition policies in several developing countries, there is little to no evidence of these policies' impact on enrollment. In part, this lack of evidence comes from data restrictions and difficulties in identifying causal effects. The bulk of the literature is observational (Torres-Cortes, 2019; Arzola, 2019; Espinoza, Gonzalez-Fiegehen, and Granda, 2019), or ex-ante analyses (Espinoza and Urzúa, 2015; Bucarey, 2018). Only a few studies use quasi-experimental methods (Molina and Rivadeneyra, 2019). Consequently, important questions about the efficiency and efficacy of these policies in improving access to college for low-income students remain unanswered.

In this paper, I had access to restricted access information in Chile that allows me to perform a fuzzy regression discontinuity (RD) design to study a free-tuition policy that benefited the poorest 50% of the population in Chile. This arbitrary cutoff introduced massive differences in the price faced by students just below and those just above the eligibility criteria. Exploiting this disconti-

[2]Some papers find that place-based policies benefit more higher-income students Abraham and Clark (2006) K2007, others find no effect on college enrollment Kane (1997), others, such as merit-based aid, tend to favor more students from wealthier backgrounds (Binder and Ganderton, 2002)

nuity, I can identify the effect of free tuition on median-income students.

The strong internal validity of the RD design comes with an equal-sized drawback: we can only estimate the effect for students in the 50% of the income distribution. We might expect that students in the lower tail of the distribution have different effects than their more affluent peers Andrews, DesJardins, and Ranchhod (2010). To address the distributional effects, I complement the RD strategy with a difference-in-difference approach, comparing eligible to non-eligible students before and after the implementation. This approach allows me to compare students at different points of the income distribution and with different skill levels. Here, the main concern comes from self-selection into applying for financial aid. As the policy created incentives for students to apply, the sample before and after the policy may differ in many observable and unobservable characteristics. I overcome this issue using two approaches. The preferred approach explicitly models the probability of financial aid application and implements an Expectation-Maximization (EM) algorithm to jointly estimate financial aid and college choice, controlling for unobserved factors.

The second approach exploits the variation in the proportion of poor students in a school. I compare students in poorer schools, who are more exposed to the policy, to those in the wealthiest schools before and after its implementation. This approach bypasses the self-selection problem by using all students in a graduating cohort, rather than just those with eligibility information, without adding behavioral assumptions. These two approaches identify related but different effects. While the first estimates the effect of free tuition on eligible students, the second does it for students in poor schools.

Results consistently show an increase in enrollment in academic programs. The difference in difference approach shows that eligible students were 7.3 percentage points (10.6%) more likely to attend any college and 6.8 points (18.1%) more likely to enroll in an academic program. The effect was larger for lower-income students, who experienced a 7.8 percentage point (20.2%) increase in academic programs. This was primarily driven by students who would not have attended college otherwise. On the other hand, high-achieving students were more likely to forgo technical college in favor of academic programs. They were also 6.4 percentage points (16.1% percent) more likely to enroll in a top-ranked program.

This paper contributes to the literature in three different ways. First, I exploit one of the few large-scale, need-based financial aid programs that are simple and salient enough to provide clear evidence of causal effects on college choices. As opposed to Pell Grant (Kane, 1997) and the Tax Deduction programs (Hoxby and Bulman, 2016) in the United States, the Chilean policy only required a simple online application and was the most notable policy during its implementation. Second, results show that failing to control for self-selection may elicit considerable bias in a difference-in-difference estimation, especially in the technical-academic program margin. This is important for any study using information from the FAFSA or any other financial aid application form. Finally, this is the first paper to estimate the causal effect of this free-tuition policy on college enrollment in Chile, providing valuable information for policymakers and researchers alike. This paper also extends the research on free-tuition policies to developing countries, where access to higher education is highly unequal and where the impact of these policies is still uncertain.

1.2 Background

1.2.1 Financial aid policies

There is rich literature studying the effect of financial aid on students' decisions at the college-going and the type-of-program margins in the United States. Using quasi-experimental methods, most of this research finds a positive and significant effect on college enrollment. In the high end, estimates suggest an increase in college enrollment of around 6 to 11 percentage points (Dynarski, 2000). A few authors find no effect on the college-going margin (Kane, 1997; DesJardins and McCall, 2014; Hoxby and Bulman, 2016). In contrast, some find an increase only for in-state 4-year colleges (Cohodes and Goodman, 2014), suggesting students would have still enrolled in college, but at a different institution.

Studying a merit-based policy, Dynarski (2000) argues that HOPE scholarship in Georgia[3] in-

[3] Hope scholarship was implemented in Georgia for the first time in 1993. It offered Georgia residents who gradu-

creased enrollment by seven percentage points, but most of this effect came from middle-high income students, and many diverted from technical colleges to in-state, four-year institutions. In a similar merit-based policy, Page et al. (2018) find that the Pittsburgh promise increased enrollment in in-state four-year public institutions by 10 percentage points, with a slight advantage for wealthier students. Other merit-based programs present similar trends, such as the Massachusetts Adam Scholarship (Cohodes and Goodman, 2014), and the New Mexico Success program (Binder and Ganderton, 2002), where the effect is dominated by middle-high income students shifting towards in-state, four-year schools.

Other financial aid programs used the place of residence - or graduation - to allocate benefits. The most prominent place-based program was implemented in Kalamazoo in 2006[4]. Bartik, Hershbein, and Lachowska (2015) find that enrollment increased by 10 percentage points in in-state 4-year institutions because of this program. Similarly, Andrews, DesJardins, and Ranchhod (2010) find that eligible students were 11 percentage points more likely to apply to a flagship university, with a more significant effect for low-income students. In a similar program, Kane (2007), studying the District of Columbia Tuition Assistance Grant, finds a significant increase in college applications and enrollment. However, grant recipients concentrated in the middle- and higher-income neighborhoods.

Finally, need-based programs use family income to allocate benefits. The effect of these programs on college enrollment is still ambiguous. While some, evaluating small-scale programs, find significant effects (Linsenmeier, Rosen, and Rouse, 2006), most of the research studying large-scale programs find no or minor effects Hoxby and Bulman (2016). This last result is usually explained by the complexity of the application process (Dynarski, Scott-Clayton, and Wiederspan, 2013), the salience of the program (Hoxby and Bulman, 2016), and the lack of information about the benefits and eligibility criteria (Dynarski and E., 2006). The policy studied in this paper provides a unique opportunity to evaluate a large-scale, need-based policy that was simple and salient

ated with a GPA of 3.0 or higher free tuition in any in-state technical institute, college, or university.

[4]The Kalamazoo Promise offered free or subsidized tuition for students who attended and graduated from a Kalamazoo Public School in high school.

and affected a diverse set of students from different socioeconomic backgrounds and skills.

The fact that merit-based programs tend to have moderate effects on college-going (Waddell and Singell, 2011) or that the benefits concentrate in middle-to-high-income students (Dynarski, 2000) has led scholars to argue that merit-aid programs channel financial assistance away from low-income students and towards those students who would have attended college anyway. We can make a similar argument for free-tuition policies. If higher-income students, who are on average better prepared for college, decide to enroll in free institutions, low-income students, who tend to perform worse in college admission tests, would be pushed towards tuition-charging or less-selective institutions.

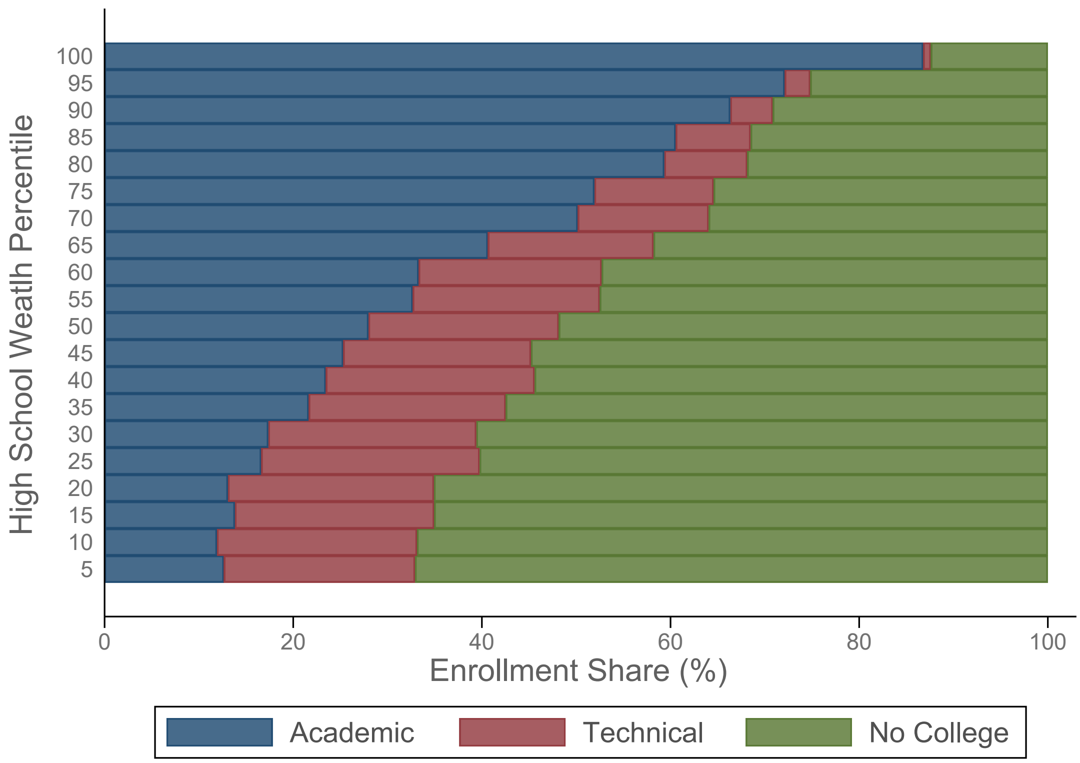
1.2.2 Higher education in Chile

When deciding to enroll in higher education, students can choose an academic or a technical track. There are three different types of tertiary education institutions: Technical Formation Centers (TFC), Professional Institutes (PI), and Universities. TFCs offer 2-3 years-long technical programs that end with a technical certificate or diploma. PIs offer technical and academic programs that last between 3 and 4 years and may end with an associate degree. Technical programs represent around 58% of Professional Institutes' total enrollment. Finally, Universities offer mostly academic programs that last between 4 and 5 years and may lead to a bachelor's degree. Universities also offer technical programs that typically last between 3 to 4 years, but these represent only 3% of Universities' total enrollment. Therefore, technical programs are highly concentrated in TFCs and PIs. Almost 93% of enrollment in technical programs is in one of these institutions.

Access to higher education has expanded significantly in Chile in the last decades, but there is still a large enrollment gap between low-income and high-income students. While the latter are more likely to enroll in college and do so in more selective and expensive programs, the former tend to concentrate on technical programs or skip college.

Using a high school ranking based on the proportion of poor students in that high school, I compare enrollment in technical and academic programs across this ranking. Figure 1.1 shows this relation for high school cohort 2014. Students from the poorest 5% schools are more likely not to enroll in college, and about 50% of those who enroll, do so in a technical program. On the other end, students from the richest 5% schools mostly enroll in academic programs, and only 21% do not enroll in college. This fact has led to important discussions regarding which type of education free tuition should target. Targeting technical education would affect mostly low-income students. However, there is still little understanding of how low-income students make these decisions and how much they are affected by economic constraints.

Figure 1.1: High School Wealth and Student Enrollment



Notes: Percentiles are constructed from a ranking of high schools based on the proportion of poor students that attend there. Poorer schools (i.e., those with a higher proportion of poor students) are in the lower percentiles. The higher the percentile, the richer the school.

Given the heterogeneous returns to higher education programs of study (Hastings, Neilson, and Zimmerman, 2013), understanding how students self-select into technical or academic programs and the role that economic constraints play in this decision can add important information on effective policies to guide students into more selective programs. In the United States, Zimmerman (2014) shows that being admitted to college in Florida led to a positive and high return for the marginal student. Furthermore, these returns were larger for low-income students. In Chile, Hastings, Neilson, and Zimmerman (2013) find that more selective programs, which are more expensive and have lower graduation rates, present the highest returns, with no critical heterogeneity by socioeconomic status. These results suggest that increasing the access to high-quality, high-risk programs for low-income students may have a substantial economic impact in the log-run.

To enroll in college, students take a centralized admission test called PSU – like the SAT in the United States – that covers language, history, science, and math. The score obtained in this test is then used to select students into the programs of their preference. The final application score combines PSU scores, high school GPA, and the student's ranking in their high school cohort. Since 2012, 36 public and private universities use a centralized admission system where an algorithm matches students to a university/program based on their preferences and admission scores. Professional Institutes and Technical Formation Centers and some private universities do not participate in the centralized process. Although these institutions also use the admission score to select students, they do it in a decentralized, independent process.

1.2.3 FUAS and income deciles

Students apply for government benefits by filling the Unique Form of Socioeconomic Accreditation (FUAS – Formulario Unico de Acreditación Socioeconómica). The FUAS is an online application where students report household income, parents' education level, and family size. The government uses this information to define the eligibility status for different scholarship and loan programs.

High school students fill the FUAS for the first time in November of their graduation year[5]. In December, they take the college admission test called PSU. In January, students know if they are eligible for any government benefit by receiving a battery of potential benefits based on their

[5]The FUAS may be filled by any student who is applying for college admission or who is already enrolled in college but want to resubmit their income information or apply for new scholarships

FUAS information. Once they know their potential benefits and their PSU scores, students apply for college in mid-January.

There is a second FUAS application process in February-March. Students may resubmit their information if their family income has changed since November or if they did not submit it in the first process. Around 15% of students submit the FUAS in this second process.

To avoid any income manipulation, The Department of Education and the Department of Social Development verify self-reported information with administrative records. Before 2016, the Department of Education used information from the Internal Revenue Service to verify income. In 2016, the Department of Social Development oversaw income verification, using multiple sources that captured a broader set of income sources. If a piece of information cannot be verified, the student must submit evidence of their claim to the Department of Education.

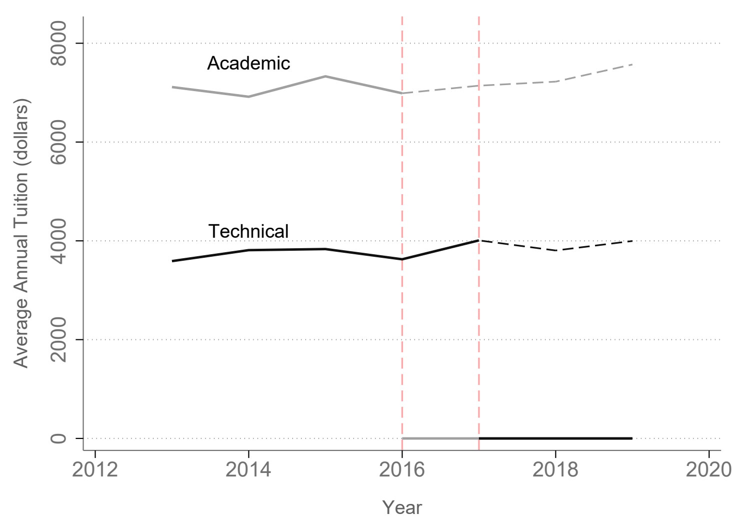
To assign each student to an income decile, the Department of Social Development uses the Socioeconomic Characterization Survey, a nationally representative survey conducted every two years, to constructs household per capita income deciles. Then, using the FUAS verified income information, students are assigned a decile if their income falls within that decile's cutoffs. Suppose a student disagrees with their socioeconomic assessment. In that case, they may appeal the decision by showing evidence of income, or lack thereof, that differs from the Department of Social Development information. Only around 5% of students appeal each year.

1.2.4 Free tuition policy

Until 2016, Chilean financial aid was mostly merit-based, requiring minimum scores or high school GPA for eligibility. With the introduction of the free-tuition policy, Chile moved towards a need-based aid, where students in the poorest 50% of the population could apply for free tuition at any public and some private Universities. The only requisites for eligibility are filling the FUAS, being in the poorest 50% of the population, and enroll in one of the eligible institutions. This benefit was extended to the poorest 60% in 2018, with the plan to get to 80% by 2022. This created discrete changes in the cost students faced when enrolling in higher education.

Figure 1.2 shows the cost scheme faced by eligible and non-eligible students before and after the policy. In the first year of implementation, only Universities were eligible institutions, making academic programs cheaper than technical programs. In 2017, the biggest TFCs and PIs were included to the policy. Because these institutions offer most of the technical programs in Chile, in 2016 it was primarily academic programs offering free tuition. Table C1 shows the list of institutions that ascribed to the policy in 2016 and 2017. There are 46 TFCs in Chile, of which six were eligible for free tuition. Similarly, only 6 of the 38 PIs were eligible. Although the number of institutions ascribed to the policy is low, these represent 59.8% of the total enrollment in TFCs and 50% in PIs. Regarding Universities, half of them ascribed to the policy, representing 62.6% of total enrollment in Universities.

Figure 1.2: Distribution of Tuition by Type of Program in 2015



Notes: Dashed line is the average tuition for students who were not eligible for free tuition. Solid line shows the change in tuition level for eligible students. In 2016, academic programs were cheaper than technical programs.

Around 140,000 students studied for free in 2016, and 35% of them were new students. Of these new students, almost 54% were recent high school graduates, while the rest spent at least one year out of school before deciding to enroll. In 2017, the number of beneficiaries grew to 260,000 students. Besides the cumulative effect from the previous year, part of this increase may be due to the inclusion of TFCs and PIs as eligible institutions or that students took time to prepare for the

PSU, delaying their application for a year.

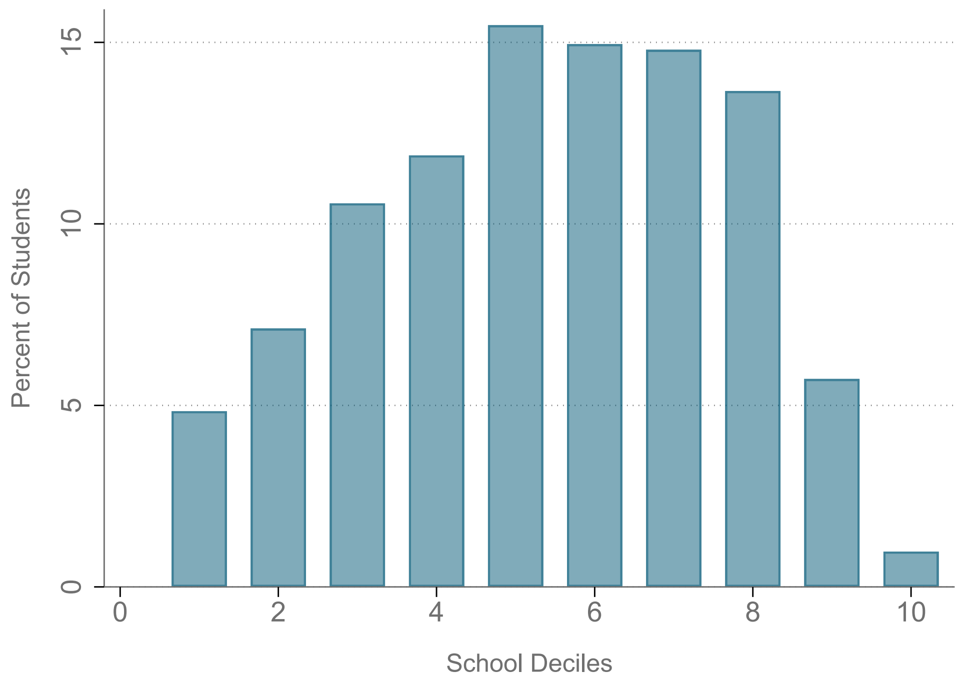
Table 2.1 describes students who received the benefits during the first two years of implementation. They come predominantly from public or subsidized (voucher) schools, and 70% of them were considered ”priority students” in high school. They tend to perform better in high school and are more likely to be first-generation students. In Figure 1.3, I ranked high schools according to how many priority students graduated from each school and plotted the distribution of students who received free tuition. If this rank somehow represents schools’ wealth, this graph suggests that students receiving free education come predominantly from the middle-high income high schools. Because higher-income students are more prepared and perform better in admission tests, many authors argued that the policy would displace low-income students (Bucarey, 2018), creating a ”phenomenon of inverted poles,” where more affluent students access to free education while pushing lower-income students towards lower-quality, tuition-charging institutions or no college at all Gayardon and Bernasconi (2016). This would increase educational inequalities. So far, there is no evidence supporting this claim, and this paper is the first attempt to fill this gap.

Table 1.1: Characteristics of Students Receiving Free Tuition

	Free Tuition (1)	Paid Tuition (2)
Female	0.50	0.51
Priority Student	0.72	0.38
Parents with Higher Ed.	0.08	0.12
Type of School		
Public	0.39	0.30
Subsidized	0.55	0.52
Private	0.02	0.14
Technical High School	0.31	0.25
Student Performance		
Top 10%	0.23	0.14
Decile 2	0.15	0.11
Decile 3	0.12	0.11
Decile 4	0.11	0.11
Decile 5	0.09	0.10
Decile 6	0.08	0.10
Decile 7	0.07	0.09
Decile 8	0.06	0.09
Decile 9	0.05	0.08
Decile 10	0.03	0.06
N	77,915	555,394

Notes: Sample is composed by all student enrolled in higher education in 2016 or 2017. I splitted the sample into two columns. Column (1) uses all beneficiaries of free tuition. In Column (2), the universe is those students who enrolled in higher education without free tuition.

Figure 1.3: Distribution of students receiving free tuition based on high school wealth

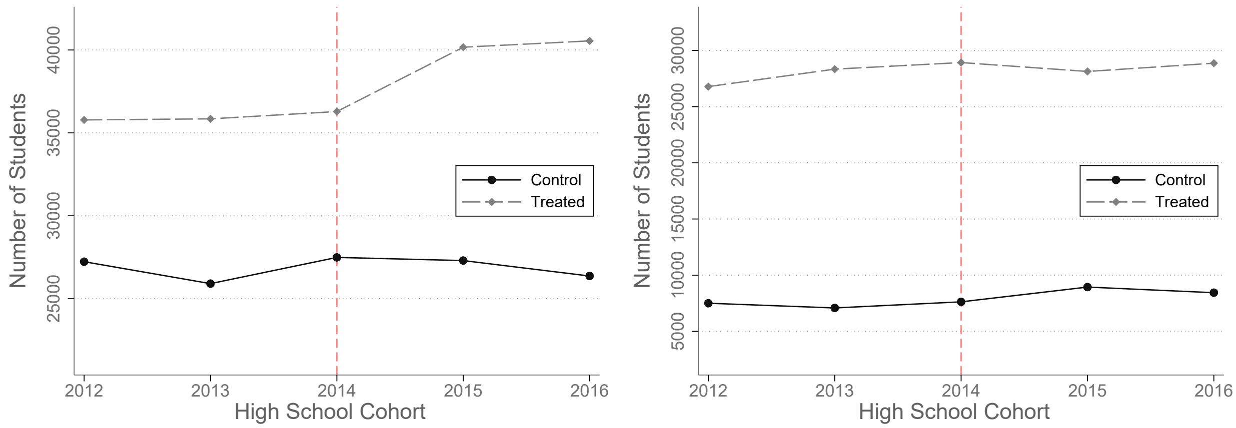


Notes: Percentiles are constructed from a ranking of high schools based on the proportion of poor students that attend there. Poorer schools (i.e., those with a higher proportion of poor students) are in the lower percentiles. The higher the percentile, the richer the school.

Few papers have tried to estimate the effect of this policy on college enrollment. (Bernasconi, 2019) uses a policy change in 2012 to estimate the elasticity of college enrollment and builds a general equilibrium model to predict the effect of the free-tuition policy. He finds that free tuition would displace low-income students to less selective programs. (Torres-Cortes, 2019) uses a multilevel analysis to study changes in application patterns for cohorts before and after the policy. Because she does not observe eligibility, she compares cohort effects before and after the policy, finding that cohorts after the policy were more likely to apply to top-ranked institutions.

In Figure 1.4, I show the total enrollment among eligible and non-eligible students. The number of eligible students going to academic programs increased while non-eligible students remained roughly the same. As we see more eligible students enrolling in college, questions remain whether these new students are low-ability who go to lower quality programs or high-ability, low-income students who missed off high-quality programs before free tuition.

Figure 1.4: Enrollment in Academic/Technical Programs Before and After the Policy by Eligibility Status



(a) Academic Programs

(b) Technical Programs

Notes: Number of recent high school graduates enrolling in academic or technical programs. The enrollment increase in academic programs for eligible students may be due to two things: an increase in financial aid application and/or an increase in enrollment per-se.

1.3 Data and Sample

1.3.1 Data

I draw information from multiple public and restricted-access sources. First, the Department of Education in Chile has de-identified, publicly available information on students' enrollment and performance at different education levels. This dataset follows students from elementary school to higher education, storing information on enrollment, performance, and school characteristics. I use this dataset to construct students' high school records and college enrollment decisions. At the high school level, the Ministry of Education identifies "priority students" to allocate government benefits, which I use as a proxy of poverty[6]. I can identify students' major, type of program (technical or academic), annual enrollment, and tuition level at the college level.

I complement this data with restricted-access information from the FUAS. I know their income

[6]The Ministry of Education classifies a student as *priority* if he meets at least one of the following criteria: a) the student is in the government program "Chile Solidario,´´ aimed for low-income families; b) she is among the poorest 33% of the population or; c) she is classified as very poor in the public health system

decile for everyone who applied for financial aid, which the Department of Education uses to allocate higher education financial aid. I use this information to identify which student was eligible for free tuition.

The Ministry of Social Development also granted me access to the households' income. This information comes from the Household Social Registree (Registro Social de Hogares), an administrative database used to allocate social policies. This database collects information from different federal ministries and agencies, such as the internal revenue services, the Ministry of Education, the Ministry of Labor, and the Ministry of Health. The Ministry of Social Development uses this household income information to create deciles that the Department of Education utilizes later to define eligibility for free tuition. I have a modified version of this income because it was considered highly sensitive.

The fourth set of information comes from the students' college application process. I see students' college admission test (PSU) scores and their preference to up to ten program/institution combinations. I construct a program quality ranking using the average PSU score in a program among recent enrollees with this dataset.

1.3.2 Sample description

I focus on students who graduated from high school in 2012 through 2016. Because free higher education may induce people to leave the labor market to enroll in college, I restrict my analysis to immediate enrollment after high school graduation. For this same reason, I drop adult-education high schools.

One million two hundred thousand students graduated from high school between 2012 and 2016, and 60% of them took the PSU and filled the FUAS right after high school graduation. Table 1 show descriptive statistics of all students who graduated high school between these years. Those who filled the FUAS were more likely to graduate from a public or voucher school, and perform better in high school and the PSU. Priority students, which I use as a proxy of being poor, are more likely to fill the FUAS and being eligible for free tuition. Around 50% of eligible students were considered *priority* the year they graduated, and 91% of priority students were eligible. I construct deciles of schools based on the proportion of priority students in a school. Using the proportion of priority students in a school, I create deciles of schools where the lower deciles have a higher proportion and are thus considered poorer schools. Table 1.2 show that eligible students come predominantly from the middle-lower deciles and usually have lower PSU scores.

Table 1.3 compares students before and after the policy implementation. I use cohorts 2013 and 2014 as the before sample and 2015 and 2016 as the after. The number of students filling the FUAS increased by 8% the years after the policy. Both the eligible and non-eligible groups expanded by two percentage points. This suggests two things. First, this policy induced students to apply for financial aid, and second, students did not know their eligibility status before applying. Otherwise, we would expect an increase primarily in eligible students.

1.4 Empirical Strategy

Because financial aid is correlated with many observable and unobservable characteristics that also affect college choices, identification is usually challenging in this context. To overcome this problem, several papers studying the effect of financial aid policies in the U.S. used a difference-in-difference approach (Dynarski, 2000; Dynarski, 2003; Andrews, DesJardins, and Ranchhod, 2010; Bartik, Hershbein, and Lachowska, 2015; Carruthers and Fox, 2016; Page et al., 2018) or a Regression Discontinuity Design (Denning, 2019; DesJardins and McCall, 2014; Hoxby and Bulman, 2016; Page et al., 2019). In this paper, I use both strategies.

1.4.1 Regression discontinuity design

I exploit the sharp discontinuity of students' eligibility for free tuition. This allows me to compare students just above the 50% threshold to those just below it. If college choice is a continuous function of family income, then the only difference between these students is that for some of them, college prices dropped significantly.

I use a fuzzy regression discontinuity design because students may appeal the original decision

Table 1.2: Summary Statistics. High school graduating cohort of 2012 to 2016

	All	FUAS	Eligible	Non-eligible
Female	0.510	0.548	0.563	0.504
Avg. GPA	5.640	5.767	5.735	5.862
Priority	0.415	0.409	0.496	0.154
Type of school				
Public	0.358	0.342	0.382	0.223
Subsidized	0.516	0.569	0.553	0.615
Private	0.086	0.050	0.020	0.141
Tech. High School	0.325	0.290	0.334	0.158
Regular High School	0.674	0.710	0.666	0.841
School Priority Deciles				
1	0.074	0.064	0.079	0.020
2	0.096	0.084	0.101	0.036
3	0.115	0.106	0.124	0.053
4	0.117	0.111	0.126	0.068
5	0.127	0.126	0.139	0.089
6	0.114	0.122	0.129	0.103
7	0.114	0.129	0.125	0.141
8	0.100	0.129	0.109	0.189
9	0.075	0.090	0.058	0.185
10	0.069	0.038	0.011	0.117
PSU Score	491.101	495.964	481.596	535.968
College Enrollment				
Tech. Program	0.170	0.252	0.280	0.167
Acad. Program	0.323	0.450	0.400	0.599
Free-tuition	0.123	0.144	0.199	0.000
N	1,200,553	716,685	536,070	180,585

Notes: Sample is composed by high school students who graduated between 2012 and 2016. School priority deciles are based on the proportion of priority (poor) students in the school. Lower priority deciles identifies poorer schools. Statistics are taken for the first year after high school graduation.

Table 1.3: Student Characteristics by Eligibility Status, Before and After the Policy

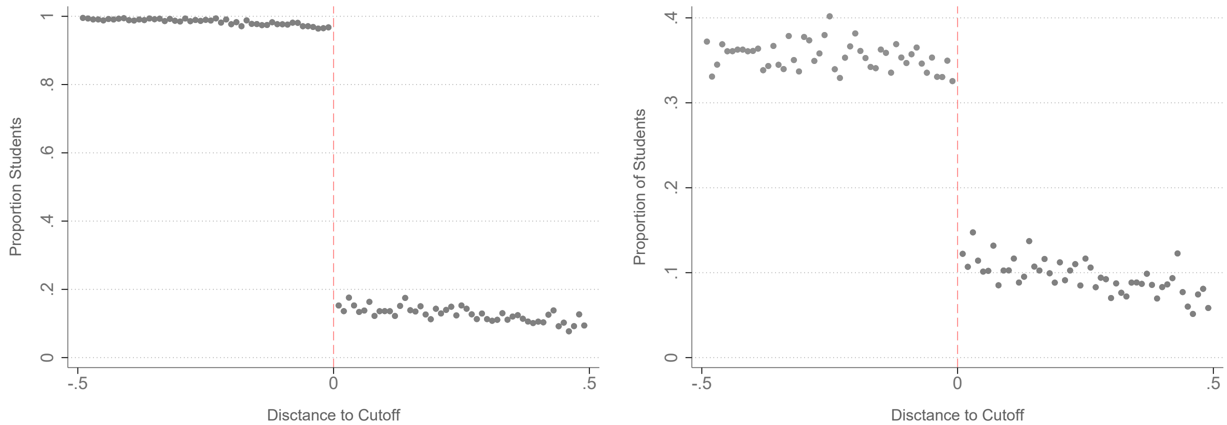
	Eligible		Non-eligible	
	Before	After	Before	After
Female	0.562	0.562	0.504	0.504
GPA	5.726	5.770	5.884	5.868
Priority	0.541	0.476	0.154	0.158
Type of school				
public	0.380	0.386	0.213	0.235
subsidized	0.555	0.551	0.629	0.600
private	0.020	0.019	0.140	0.141
PSU Score	481.3	481.9	542.6	529.2
College Enrollment				
Tech. Program	0.290	0.272	0.168	0.167
Acad. Program	0.397	0.401	0.640	0.552
N	209,874	223,655	65,888	80,645

Notes: Eligible students are those bellow the 50% income threshold. Sample is restricted to students who filled the FUAS, because only for them I have eligibility information. I use cohort 2013 and 2014 as the "Before" sample, and cohorts 2015 and 2016 as the "After" sample.

by showing evidence of income that contradicts the Ministry of Social Development's original ranking. Besides, the Ministry of Education may change eligibility status when they receive new income information. This means that my running variable does not perfectly identify eligibility, and some students who are above the threshold may end up being eligible.

Figure 1.5 shows the proportion of eligible students by bins of the running variable. There is a clear discontinuity at the threshold, providing important exogenous variation in the eligibility status of a student.

Figure 1.5: Discontinuity of Eligibility at the Threshold for the 2017 High School Cohort



(a) Eligibility Status (b) Beneficiaries of Free Tuition

Notes: Students in 2016 high school cohort are grouped by bins of 0.01 standard deviations of the running variable. Each point represent the proportion of students in each bin that is eligible (panel A) or received free tuition (panel B).

Exploiting this discontinuity, in the first stage, I run a regression of eligibility using the corrected household income as the running variable, and the 50% threshold as the discontinuity.

$$elig_i = X_i\beta_c + \gamma_{1,c}S_i + \gamma_2 1(S_i < 0) + f(S) + \beta X_i + u_{i,c} \tag{1.1}$$

Where, $elig_i$ indicates whether the student was eligible according to FUAS information, and S_i is household income, normalized to be zero at the cutoff and having a standard deviation of unity, and $f(S)$ is a flexible functional form of income.

The second stage uses the first stage results to run the following linear probability model for each outcome of interest

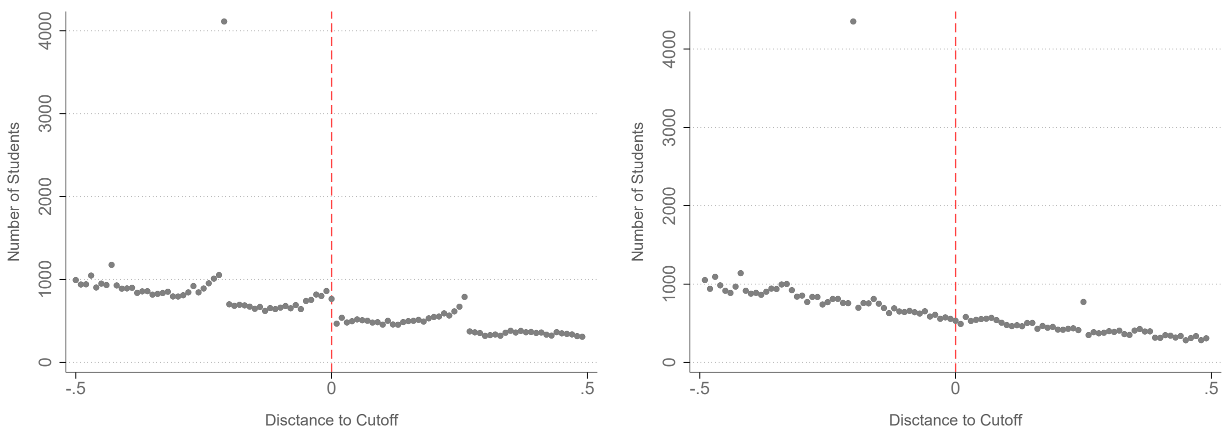
$$y_i = X_i\beta_c + \gamma_1 \hat{elig}_i + \gamma_2 1(S_i < 0) + f(S) + \beta X_i + u_i \tag{1.2}$$

Where y_{ic} is the outcome of interest, for example, choosing a technical program. The parameter of interest is γ_1 that represents the difference in the outcome of interest induced by the policy.

I use cohort 2015 and 2016 to run separate regressions and I restrict my sample to a bandwidth selected using Calonico et al. (2017) method. Nevertheless, I estimate these models for different bandwidths for robustness check.

One potential threat to identification is score manipulation by students. In Figure 1.6, I show that the density of students is smooth at the cutoff for cohort 2016, suggesting there is no manipulation at the threshold. To test this, I perform a Maccrary test of manipulation of the running variable. Consistent with Figure 1.6, I fail to reject the null hypothesis of no manipulation, at the threshold. On the other hand, cohort 2015 shows some signs of potential manipulation, which limits the validity of a regression discontinuity design. For this reason, I will focus mostly on cohort 2016 in the main results.

Figure 1.6: Manipulation of Running Variable



(a) Cohort 2015 (b) Cohort 2016

Notes: Students are grouped by bins of 0.01 standard deviations of the running variable. Each point represent the number of students in each bin for 2015 high school cohort (panel A) and 2016 high school cohort (panel B). Whenever the household's income was missing or inconsistent across administrative records, the Ministry of Social Development assigned a decile based on a set of variables that reflect long-term household income. When assigned to a decile, they were given the highest income in that decile. In 2017, the Ministry of Social Development had a larger set of administrative records, reducing the need to use imputing values.

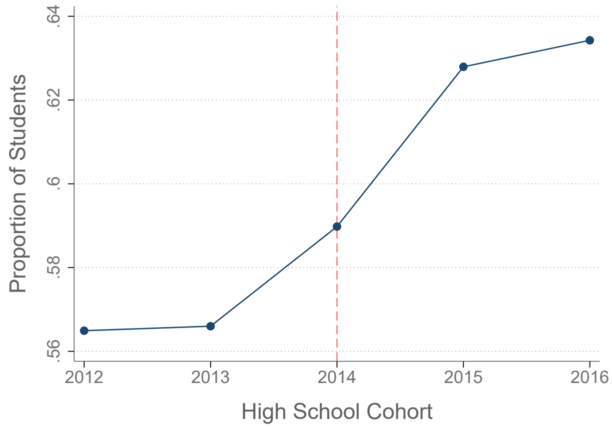
1.4.2 Difference in difference approach and distributional effects

Despite the strengths RD presents for identifying causal effects, one main drawback is the limited inference it provides for students distant from the selection margin. Hence, to study the distributional effects of free tuition, I use a Difference-in-Difference approach (DID). Comparing eligible to non-eligible students before and after the policy, controls for unobservable, time-invariant characteristics of eligible and non-eligible students, as well as time-variant characteristics that affect all students.

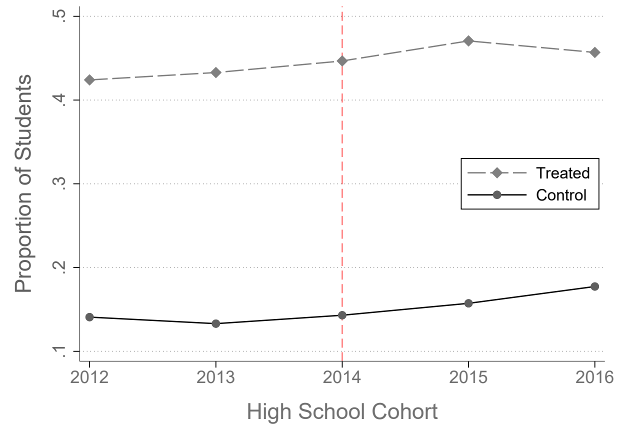
The main assumptions behind a DID approach are parallel pre-trends and no confounding changes in the treatment (or control) group at the time of the policy implementation. In other words, we assume that the difference between the treatment and control group would have remained constant in the absence of the policy. This assumption may be particularly troubling when information comes from financial aid applications. Because we only see students who decided to apply, unobservable characteristics may be affecting both financial aid decisions and college choice. If the policy induced more price-sensitive students to apply, then the sample before and after the policy would differ significantly, which may bias the results.

It is difficult to sign this potential bias a priori. On the one hand, if only eligible students reacted by filling the FUAS, the proportion of enrollees may drop in the treatment group, even if total enrollment increased. In this case, the results will underestimate the effect of the policy. On the other hand, as students do not know their eligibility status – nor the eligibility cutoff – when filling the FUAS, we may expect both the control and treatment group to expand their FUAS application. In fact, both the treatment and control group increased by about two percentage points, which represents a 6% in the treatment group and almost 10% in the control group, as shown in Figure 1.7. Because induced students are more price-sensitive than always takers, many in the control group will decide not to enroll once they know their eligibility status. In this case, we would be overestimating the effect of the policy. Which effect is larger is an empirical question, and the magnitude of the potential bias will depend on how much the policy affected the decision to complete the FUAS. The main challenge is, then, to correct this self-selection.

Figure 1.7: Proportion of Students Filling FUAS over Time



(a) All students



(b) By treatment Status

Notes: Sample is high school graduates students. A high school cohort is defined by the year the student exit high school. Students enroll in college the year after high school graduation. The policy was implemented in 2016, which means the first cohort to be affected was cohort 2015. Panel (a) show an increase in the proportion of students applying for financial aid after the policy implementation. Panel (b) shows the proportion of eligible and non-eligible students over the total of high school graduates

1.4.2.1 Selection model

To solve this issue, the main approach in this paper explicitly models the probability of filling the FUAS as a function of the policy and jointly estimates this probability and students' college choices, controlling for unobserved factors that affect both decisions. This approach uses a classical sample selection model (Heckman, 1979) consistent of two equations: The selection equation that captures the decision to fill the FUAS, and the choice equation, which models students' college decisions. Both decisions are correlated through an unobserved factor that I estimate using an Expectation-Maximization (EM) algorithm.

Selection equation. When modeling the probability of filling the FUAS, I capture the effect of the policy by including cohort fixed effects and their interaction with several student and high school characteristics. The self-selection equation is given by

$$FUAS = (X_i\beta_1 + S_i\beta_2) \times \left(1 + \sum_{m=2012}^{2016} \gamma_m C_m\right) + \delta_r + \nu ik \tag{1.3}$$

Here, X contains students' characteristics, such as whether she was a priority student, their high school and middle school GPA, GPA ranking, and their sex. High school characteristics are collected in S. Here, I include the proportion of priority students and the type of high school (private, charter, or public). C_m and δ_r are cohort and regional fixed effects, respectively.

Choice equation. The second equation captures the effect of the policy on students' decisions to enroll in college and the type of program they choose. For student i in cohort m, the latent utility of choosing option c, conditional on having filled the FUAS, is

$$y_{im,c} = X_i\beta_c + \gamma_{1,c}T_i + \sum_{m=2012}^{2016} [\gamma_{2m,c}C_{im} + \gamma_{3m,k}(T_i \times C_{im})] + \delta_r + \epsilon_{ik} \tag{1.4}$$

Where y is the latent utility of choosing option c in the outcome of interest[7], the first year after their high school graduation. Student-specific characteristics, in X, include high school GPA, GPA ranking, sex, attendance rate, priority status, and if they attended a public, charter, or private school. The treatment variable, T_i, takes the value of 1 if the student is below the fifth decile and zero otherwise. C_{im} are dummies for the year of high school graduation. Regional fixed effects are captured by δ_r. The parameter of interest here is γ_3, the difference between the control and treatment group in cohort m, compared to the baseline cohort of 2014, the cohort just before the policy implementation.

The error terms in (1.3) and (1.4), ϵ and ν, are assumed to be correlated through a single factor,

[7]The main outcomes of interest are the type of program they choose (technical, academic, or no college) and the quality of the program

η, that captures unobserved heterogeneity affecting both financial aid and college decisions.

$$\begin{aligned}\epsilon_i &= \rho_\epsilon \eta_i + u_{i,\epsilon} \\ \nu_i &= \rho_\nu \eta_i + u_{i,\nu}\end{aligned}$$

Estimation. From equation (1.3) and (1.4), I estimate the likelihood function specified in Appendix B using an Expectation-Maximization (EM) algorithm that includes unobserved heterogeneity affecting both the probability of completing the FUAS and college choices.

I approximate the unobserved heterogeneity, η, to represent different types of students, and perform the estimation using 4, 6, and 8 types. This avoids imposing distributional assumptions on the latent factor (Mroz, 1999). The EM algorithm procedure is explained in Appendix C.

Identification and Assumptions. The main assumption in this selection model is the conditional independence of eligibility and the probability of filling the FUAS. Because students do not know their eligibility status when filling the FUAS, they can only imperfectly approximate the probability of being eligible. By interacting the cohort fixed effects with students' characteristics, I am modeling the selection into FUAS as a function of the expected benefits the student may get. Students self-select based on their probability of being eligible and not on eligibility per-se. This, which implies conditional independence between eligibility and FUAS, is consistent with Figure 1.7, which shows that both eligible and non-eligible students increased their FUAS application, suggesting they can only imperfectly approximate their eligibility.

Identification in this model comes from its nonlinear structure and the use of exclusion restrictions (Wooldridge, 2010). I use the interaction between student characteristics and cohort fixed effects as exclusion restrictions. For identification, I need these student characteristics to influence the probability of filling the FUAS differently before and after the policy while having a constant effect on college choice, after controlling for eligibility and unobserved heterogeneity. Furthermore, the assumed functional forms in the error terms, conditional on unobserved heterogeneity, provide additional identification of the model (Heckman, 1979; Mroz and Savage, 2006).

1.4.2.2 Alternative Strategy: High School Level Variation

Because causal identification depends on some behavioral assumptions, I provide an alternative strategy where none of these assumptions need to hold. Instead of using eligibility status, I use school-level information to rank schools based on how poor/rich they are. I then compare students in poorer schools to students in wealthier schools before and after the policy. This allows me to compare every student who finished high school and not only those who filled the FUAS.

Using “priority student” as a proxy for being poor, I create deciles of high schools according to the proportion of priority students who graduated from each high school. The lowest decile represents the poorest 10% of high schools, i.e., those with the highest proportion of priority students. The intuition behind this approach is that students in poorer schools are more exposed to the policy than students in wealthier schools. Furthermore, this approach captures peer effects and other school-level effects that may influence students’ decisions (Perna, 2006, Bank, 2012, Torres-Cortes, 2019).

Table C2 shows that almost 90% of students in the poorest schools were eligible for free tuition, while in the richest school decile, only 5.6% were. This shows there is enough variation in exposure to the policy among the constructed school deciles.

The main specification is as follows. For student i, in cohort m and in school decile j, the latent utility of choosing option c is

$$y_{imj,c} = X_{i1}\beta_c + S_{i1}\delta_{1,c} + \sum_{j=1}^{9} \delta_{2j,c} D_s^j + \delta_{3m,c} C_{im} + \sum_{j=1}^{9} \gamma_{jm,c}(D_s^j \times C_{im}) + \delta_r + \epsilon_{I,c} \tag{1.5}$$

Where C_{im} is a dummy indicating if the student was in cohort m, and D_{sj} indicates if school s was in decile j. I use cohort 2014, and schools in the tenth (richest) decile, as the baseline. Therefore, γ_{jm} shows changes in enrollment patterns for students in school decile j, relative to the richest decile, in cohort m compared to cohort 2014.

1.5 Results

When making the transition to tertiary education, high school students face many sources of uncertainty that influence their decision to enroll in college. They must further choose if they enroll in technical or academic programs, or between a more selective, more expensive program, or a less expensive, less selective one. In this section, I present results on the effect of free tuition on two different outcomes: access to higher education and college quality.

I use two different quasi-experimental approaches: a Regression Discontinuity Design and a Difference-in-Difference approach. Using RD allows me to estimate the effect for students at the margin of being eligible, while the DID provides the opportunity to get the distributional effects of the policy.

1.5.1 Effects for student at the margin

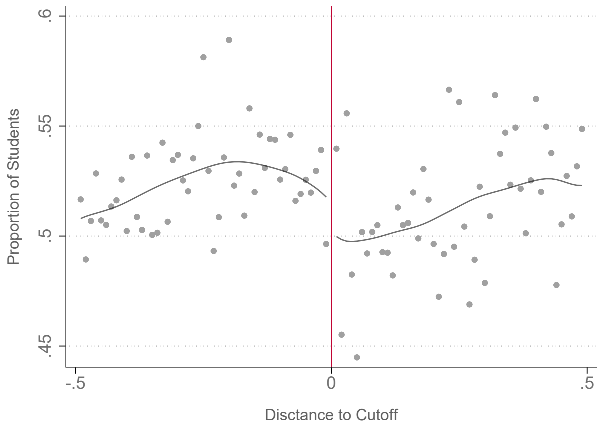
I start with the results from the regression discontinuity design for students at the margin of being eligible.

1.5.1.1 Access to higher education and college choice

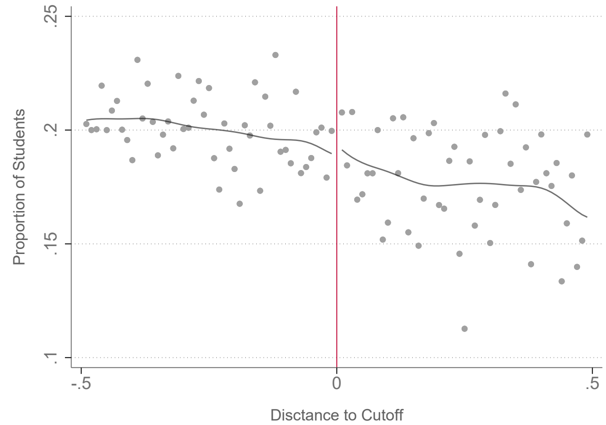
Figure 1.8 shows the relation between family per capita income and college enrollment. As family income increases, the chances of enrolling in academic programs increases. The discontinuity at the threshold is interpreted as the causal effect of free tuition on college enrollment for students at that margin.

These results are quantified in Table 1.4. Panel A shows that eligible students were 2.6 percentage points more likely to attend an academic program, and 2.7 less likely to enroll in a technical program for cohort 2015, when only academic programs were free. For cohort 2016, where both academic and technical programs where free, enrollment in any college increased by 2.1 percentage points, driven by an increase in both technical and academic programs.

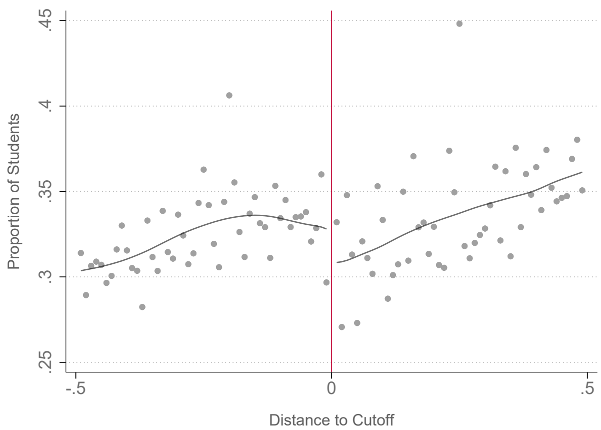
Figure 1.8: The Effect of Free Tuition on College Choice. Regression Discontinuity Design



(a) Any College



(b) Technical Programs



(c) Academic Programs

Notes: Students in 2016 high school cohort are grouped by bins of 0.01 standard deviations of the running variable. Each point represent the proportion of students in each bin that enrolled in any college, technical programs and academic programs. The line represents a nonparametric estimation of the correlation between income and the relevant outome.

Despite the magnitude of the effects, these are not statistically significant, suggesting there is important variation around the cutoff. In table 1.5, I expand the bandwidth for the local regression, in doing so, these effects get larger as we start capturing the enrollment trend of poorer students. Considering that students had little space to manipulate their income, this suggests that the effects are larger for lower-income students, who are usually more susceptible to financial aid.

Table 1.4: The Effect of Free Tuition on College Choice for Students at the Margin

	First Stage	Second Stage		
	Eligible	College	Technical Program	Academic Program
A. Cohort 2015				
Eligible	0.641***	-0.001	-0.027	0.026
	(0.008)	(0.020)	(0.017)	(0.018)
N	21,516			
B. Cohort 2016				
Eligible	0.815***	0.021	0.006	0.015
	(0.006)	(0.014)	(0.011)	(0.012)
N	36,243			

Note: Different regressions were fitted for each outcome. Coefficients show the discontinuity at the threshold, using household income as the running variable. The dependent variable in the first stage is the final eligibility status used by the Department of Education to allocate free-tuition. The second stage uses a linear probability model to estimate the effect of being eligible on the type of program students choose. I use an optimal bandwidth of 0.24 standard deviations from the cutoff, for cohort 2016, and 0.2 standard deviations for cohort 2015. These optimal bandwidth were calculated using Calonico et al. (2017).
Standard errors are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1.5: Regression Discontinuity Robustness Check to Bandwidth Selection

	Any College	Technical Program	Academic Program
Optimal Bandwidth: 0.24 SD from cutoff			
Eligible	0.0198	0.0044	0.0154
	(0.0134)	(0.0109)	(0.0120)
N	36,243	36,243	36,243
Bandwidth: .35 SD from cutoff			
Eligible	0.0477***	0.0127	0.0349***
	(0.0110)	(0.00884)	(0.00982)
N	54,102	54,102	54,102
Bandwidth: .4 SD from cutoff			
Eligible	0.0480***	0.0110	0.0369***
	(0.0104)	(0.0084)	(0.0094)
N	59,533	59,533	59,533

Note: Different regressions were fitted for each outcome. Each panel uses a different bandwidth for the local regression. All panels use a linear regression with different slope to the left and right of the cutoff Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

1.5.2 The distributional effects of free tuition

Because the previous results cannot be extended to lower-income students, I now focus on the difference-in-difference estimations, where I can identify the distributional effects of the Chilean free-tuition policy.

1.5.2.1 College choice

Table 1.6 shows the effect of the policy on three outcomes: no college, enrollment in technical programs, and enrollment in academic programs. I present the coefficients for the two first cohorts affected by the policy. For cohort 2015, only academic programs were free, while for cohort 2016 both technical and academic programs were eligible for free tuition. The policy induced students to enroll in both technical and academic programs, by 2.3 and 5.6 percentage points, respectively, when both programs were free. For cohort 2015, enrollment in any college experienced a smaller increase compared to cohort 2016, and almost half of the expansion in academic programs came from students leaving technical college. This difference suggests low-income students were less prepared (or motivated) for college, and including technical education expanded their opportunities to access higher education.

Panels B - D of table 1.6 use subsamples of economically disadvantaged and high-achieving students. In Panel B I restrict my sample of eligible students to those in the bottom 40% of income. Enrollment in any college increased by 8.6 percentage points (20.8%) and 7 percentage points (32%) in academic programs, for cohort 2016. These estimates are much larger than for the average student, which may suggest two different things. First, these students may have lower-expected returns to education and thus, enrolled in college when costs were lower; or second, they face higher economic constraints, and taking loans was not a viable option. In contrast, students in the middle of the distribution experienced a moderate effect on academic enrollment. Interestingly, in the 2015 cohort, these students were 1 percentage point less likely to attend any college. Although this effect is not statistically significant, this may suggest some middle-income students were displaced by lower-income, high-achieving students. In the 2016 cohort, when less selective institutions were included, college enrollment increased by 1.2 percentage points for these students.

In Panel D, I use a subsample of students who ranked in the top 20% GPA in high school. These students were 6.3 percentage points more likely to attend any college, and many of those induced to enroll in an academic program would have gone to a technical college in the absence of the policy. The larger effect on academic programs, compared to the average student, shows that high skill students, who have higher expected returns to education, were more likely to move in the technical-academic margin when education was free.

Figure 1.10 shows the enrollment change in free and non-free institutions. Using the 2014 cohort as the baseline comparison, Figure 1.10 shows that eligible students were 10.3 percentage points more likely to enroll in a free academic program. Of those, around 50% would have enrolled in a non-free academic program in the absence of the policy.

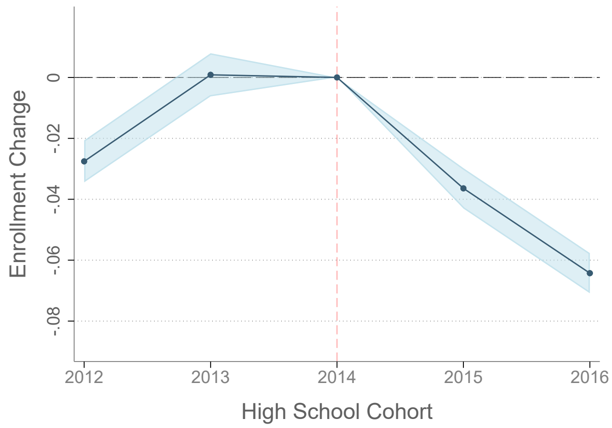
Despite this shift into free academic programs, there is no evidence of lower-income students

Table 1.6: The Effect of Free Tuition on College Choice. Difference-in-Difference Results With Correction for Self-Selection

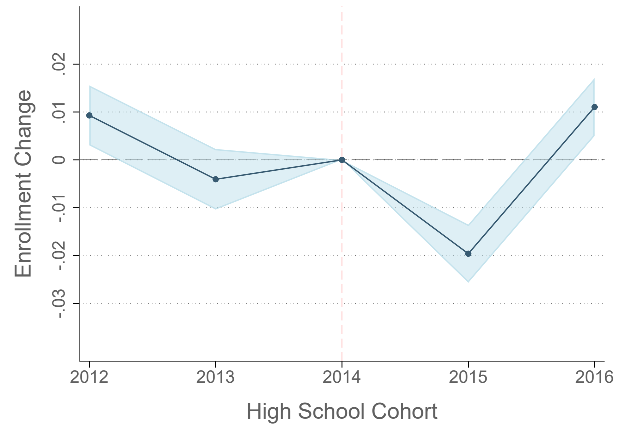
	No college	Technical Program	Academic Program
	(1)	(2)	(3)
A. All Students			
Eligible × C_{2015}	-0.0397***	-0.0092***	0.0489***
	(0.0034)	(0.0031)	(0.0039)
Eligible × C_{2016}	-0.0732***	0.0048	0.0684***
	(0.0036)	(0.0031)	(0.0039)
	[0.331]	[0.269]	[0.400]
B. Students in the bottom 40% (Low Income)			
Eligible × C_{2015}	-0.0481***	-0.0061*	0.0542***
	(0.0037)	(0.0031)	(0.0040)
Eligible × C_{2016}	-0.0853***	0.0078**	0.0775***
	(0.0037)	(0.0031)	(0.0041)
	[0.343]	[0.273]	[0.383]
C. Students between 40 and 50%			
Eligible × C_{2015}	-0.00208	-0.0202***	0.0222***
	(0.0056)	(0.0038)	(0.0062)
Eligible × C_{2016}	-0.0249***	-0.0066*	0.0315***
	(0.0056)	(0.0038)	(0.0062)
	[0.258]	[0.242]	[0.500]
D. High-Achieving Students			
Eligible × C_{2015}	-0.0402***	-0.0230***	0.0632***
	(0.00667)	(0.00499)	(0.00765)
Eligible × C_{2016}	-0.0624***	-0.0129**	0.0753***
	(0.00667)	(0.00511)	(0.00770)
	[0.220]	[0.186]	[0.593]
E. Low-income, High-Achieving Students			
Eligible × C_{2015}	-0.0482***	-0.0232***	0.0714***
	(0.0070)	(0.0051)	(0.0080)
Eligible × C_{2016}	-0.0733***	-0.0146***	0.0879***
	(0.0070)	(0.0053)	(0.0080)
	[0.230]	[0.194]	[0.576]

Note: Estimates come from the interaction of cohort fixed effects and eligibility status in a multinomial logit model, after controlling selection into financial aid application. I use cohort 2014 as the baseline cohort. I present the results for the two cohorts after the policy implementation, cohort 2015 (C_{2015}) and cohort 2016 (C_{2016}). Panel A uses every student who finished high school between 2012 and 2016. Panel B restricts the sample ef eligible students tot hose in the lowest 40% of the income distribution. Panel C uses students between the 40 and 50% of the distribution. Panel D focus on students who graduated with the top 20% GPA in their cohort. Panel E uses students below the poorest 40% and in the top 20% GPA in their high school cohort. For each panel, I run a separate selection models with the respective sample.
Bootstrap standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

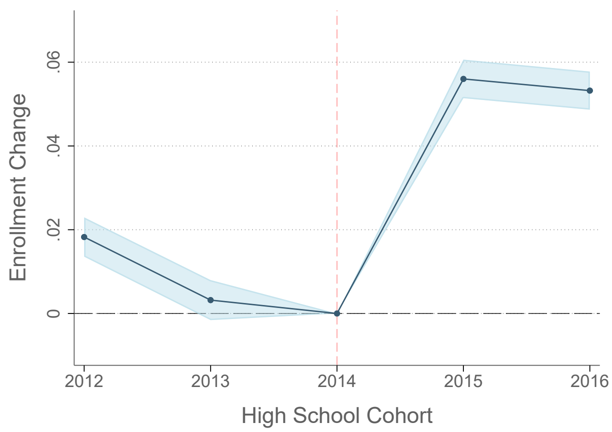
Figure 1.9: The Effect of Free Tuition on College Choice. Difference-in-Difference Approach



(a) No College



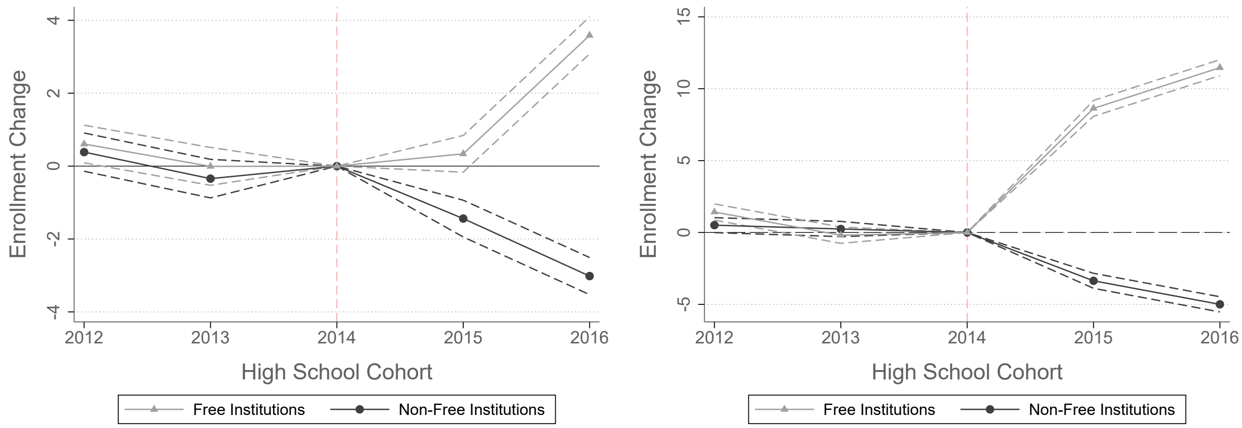
(b) Technical Program



(c) Academic Program

Notes: Each point represent the coefficient of the interaction between the cohort fixed effect and eligibility status. The shaded area represent the 95% confidence interval. Eligible students increased their enrollment in academic programs by almost 6 percentage points relative to non-eligible students, compared to cohort 2014.

Figure 1.10: Enrollment Change in Free and Non-Free Institutions. Difference-in-Difference Approach



(a) Technical Program

(b) Academic Program

Notes: Each point represent the coefficient of the interaction between the cohort fixed effect and eligibility status. The shaded area represent the 95% confidence interval. Coefficients come from a multinomial logit with 5 different choices: no college, technical program in free institution, technical in non-free institutions, academic program in free institution, and academic program in non-free institutions.

being crowded-out of college. In fact, the effect on low-income students did not change when free tuition was expanded to the poorest 60%, in 2017. Despite including richer students in the policy, we do not see a displacement of poorer students towards lower-quality or tuition-charging institutions.

Because these results may be sensitive to behavioral assumptions, I present multiple robustness checks and alternative strategies in Appendix B. Results consistently show that lower-income students were more likely to enroll in any college after the policy implementation.

Together, these results suggest that access to higher education is conditioned by economic constraints, and providing free tuition induced low-income, high achieving students to enroll in academic programs in place of technical education. Students who were not high-achievers also experienced a significant enrollment gain in college-going, especially when technical education was available for free.

1.5.2.2 College quality

I now examine the distributional effect of free-tuition policies on access to selective programs. I ranked programs based on the average PSU score of admitted students, and estimate the probability of enrolling in a top-tier program. To simplify the estimation, I group programs into 4 tiers: top 20%, 20-40%, 40-60%, and bottom 40%.

Table 1.7 shows enrollment changes in programs across these tiers. Column (1) shows institutions in the top 20%, while column (4) represents those least selective programs. Panel (A) of Table1.7 suggest eligible students were more likely to attend programs in the top 20%. In the 2015 cohort, enrollment in top-ranked programs was partly driven by a decline in lower-ranked programs, while in the 2016 cohort, when less selective institutions were included, enrollment grew across the whole ranking distribution.

Table 1.7 also shows important heterogeneity by students' skills. High-achieving students, shown in panel C), were 6 percentage points more likely to attend a top-ranked program after the policy took place. This is twice as large as for the average student, suggesting that students with higher expected returns to college were not attending selective programs when tuition was in place[8].

Conclusion

In 2016, Chile waived tuition in selected higher education institutions for the poorest 50% of the population. Because there were no academic requirements and the policy affected families from a wide range in income distribution, this massive change in college prices provides a unique opportunity to study the distributional effect of free college.

I use different strategies to estimate the effect of this free-tuition policy on students' decisions to attend college and the type of college they choose. A fuzzy regression discontinuity approach shows that for the median-income student, this policy had a small and statistically insignificant effect on college-going. The effect was higher as I expanded the bandwidth for the local regression.

[8] A a reference, programs in the top 20% cost twice as much than programs in the bottom 40%

Table 1.7: The Effect of Free tuition on Access to Selective Programs. Difference-in-Difference Approach With Correction for Self-Selection

	Enrollment			
	Top 20%	20 - 40%	40 - 60%	60 -100%
	(1)	(2)	(3)	(4)
A. All				
Eligible $\times C_{2015}$	0.0365***	0.0183***	-0.00477*	-0.0136***
	(0.00290)	(0.00275)	(0.00284)	(0.00376)
Eligible $\times C_{2016}$	0.0422***	0.0129***	0.0120***	0.00381
	(0.00296)	(0.00276)	(0.00297)	(0.00372)
	[0.186]	[0.104]	[0.137]	[0.242]
B. Students in Bottom 40%				
Eligible $\times C_{2015}$	0.0395***	0.0204***	-0.00334	-0.0115***
	(0.00305)	(0.00287)	(0.00293)	(0.00386)
Eligible $\times C_{2016}$	0.0471***	0.0161***	0.0128***	0.00660*
	(0.00312)	(0.00289)	(0.00307)	(0.00381)
	[0.173]	[0.100]	[0.135]	[0.247]
C. High Skill Students				
Eligible $\times C_{2015}$	0.0646***	0.0160***	-0.0148***	-0.0297***
	(0.00726)	(0.00550)	(0.00524)	(0.00647)
Eligible $\times C_{2016}$	0.0641***	0.0102*	-0.00320	-0.0123*
	(0.00729)	(0.00538)	(0.00555)	(0.00655)
	[0.399]	[0.103]	[0.115]	[0.163]
D. Low-income, High Skill Students				
Eligible $\times C_{2015}$	0.0683***	0.0182***	-0.0124**	-0.0296***
	(0.00754)	(0.00569)	(0.00537)	(0.00662)
Eligible $\times C_{2016}$	0.0706***	0.0132**	-0.00266	-0.0114*
	(0.00759)	(0.00556)	(0.00570)	(0.00670)
	[0.380]	[0.103]	[0.116]	[0.170]

Notes: Coefficients come from a multinomial logit model using the ranking of the program were the student enrolled/applied as dependent variable. I split this ranking into 4 categories: top 20%, between 20-40%, 40-60%, and bottom 40%. Not shown in the results is the effect on any-college, to which all these coefficients should add up. I show the results for the first two cohorts after the policy implementation, suing cohort 2014 as the baseline. Panel A uses every student who finished high school between 2012 and 2016. Panel B restrict the sample to students in the lowest 40% of the income distribution.Panel D focus on students who graduated in the top 20% in their cohort. For each panel, I run a separate selection model. Outcome means for the relevant baseline subsample are shown in square brackets.
Bootstrap standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Students were between 1.5 and 3.3 percentage points more likely to attend college, depending on the bandwidth used. Consistent with these results, a difference-in-difference approach using only students in the middle of the income distribution, shows that these students increased their overall enrollment by 2.5 percentage points and their enrollment in academic programs by 3.1 percentage points.

The Difference-in-Difference approach allows us to use the full income distribution and, thus, focus on the distributional effects of free tuition. Results show important heterogeneity by income level. In the preferred strategy, that corrects for self-selection into applying for financial aid, I find a 7.3 percentage points increase in total enrollment and a 6.9 percentage points increase in academic programs for eligible students. This represents a 10% and 18% increase from the respective baseline. This effect was higher for students facing larger economic constraints (i.e. lower income), who were more likely to attend both technical and academic programs.

Furthermore, the largest effect was found for low-income, high-achieving students. Although these students were more likely to attend college in the absence of the policy, many decided to forgo technical programs to enroll in academic, more expensive, more selective programs. This is consistent with the idea that lower-income students are under-matched because of tuition levels (Hoxby and Avery, 2013).

Using an alternative strategy where I exploit high-school level variation in the proportion of poor students in the high school, I find similar results: students in the poorest schools were more likely to enroll in both technical and academic programs.

These results are consistent with several estimations examining financial aid policies in the United States. Similar to Page et al. (2018) and Bartik, Hershbein, and Lachowska (2015) estimates, I find an 11-percentage point enrollment increase at eligible, four-year (academic) institutions, placing this policy at the higher-end of the literature on the effect of financial aid on college enrollment. In contrast to Page et al. (2018), who examines a merit-based program, and in line with Bartik, Hershbein, and Lachowska (2015), who examines a place-based program, I find that this increase in enrollment was driven mostly by lower-income students.

Methodologically, this paper emphasizes the fact that local regressions, such as RDD, hide important heterogeneity that should be considered when evaluating policies. Taking this paper as an example, RDD results suggest small effects on college-going, while DID, which uses the whole set of eligible students, shows significant and large effects. The main reason for this difference is that median-income students had significantly smaller effects than their lower-income counterparts. Given that students' skill is also a source of heterogeneity, this issue is a problem whether selection is based on income or test scores.

I also show that Difference-in-Difference estimations using information from financial aid applications, may be biased if the policy affected students' financial aid decisions, and estimations should include a correction for this self-selection. Comparing the standard DID and the self-selection corrected, we find a non-trivial bias of around 1.2 percentage points (17%) for enrollment in academic programs.

This paper does not attempt to provide a thorough evaluation of the Chilean policy. Instead, it is limited to show that low-income students face economic constraints even in the absence of credit constraints. This is consistent with the presence of decreasing absolute risk aversion in the investment in education. Results in this paper are a small piece in the puzzle that is free-tuition policies in developing countries, and further work is needed to fully understand the benefits and costs of free tuition.

Chapter 2

Free Tuition in Chile: Who Benefits and Where Do They Go?

2.1 Introduction

In 2016, after a series of student marches demanding free higher education and amid a considerable political and social upheaval, the Chilean government eliminated fees in public universities for a portion of the population. This benefit was intended for the poorest 50% of the country, with the commitment to gradually advance towards universal free tuition.

The purpose of this policy was, on the one hand, to alleviate the student debt that plagued many families and, on the other, to improve access to college for vulnerable students. It is in this last objective where most of the debate still holds. Many have argued that higher-income students would benefit the most from free tuition as they tend to be better prepared for college admission tests and may end up displacing vulnerable students toward lower-quality programs, exacerbating the inequality in access to higher education.

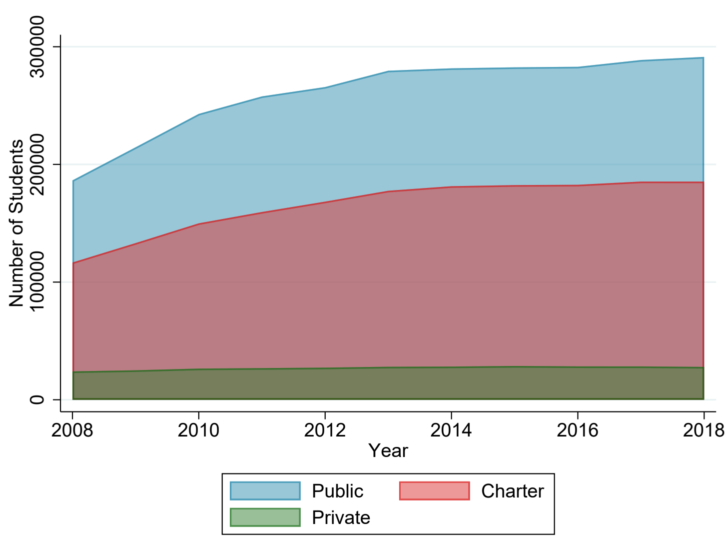
This study aims to take the first step to understand how free tuition affected the decisions and well-being of the most vulnerable students. I show that the beneficiaries of the policy concentrate in middle to low-income neighborhoods, and they were more likely to graduate from public schools, but not from the most vulnerable ones. In 2016, when the policy only included academic programs, beneficiaries were mostly high-performance students. On average, they scored over one standard deviations above the average score in the college admission test. When the policy was extended to Professional Institutes and Technical Formation Centers (technical programs), the proportion of more vulnerable students grew significantly, suggesting greater democratization of higher education.

There is an evident heterogeneity regarding which programs choose students who received free tuition. While more affluent students tend to go to more selective programs, those who attend technical education tend to come from more vulnerable backgrounds. Much of this is due to differences in performance on the college admission test. However, free tuition allowed low-income and high-performance students to access selective programs, which tend to have higher expected returns. This helps reduce the mismatch between the skills of vulnerable students and the program's quality in which they enroll.

2.2 Access to Higher Education in Chile

Access to higher education in Chile has grown considerably in the last 15 years (Espinoza and Urzua, 2015), accompanied by a reduction in the gap between rich and poor students. This reduction is partly explained by the increase in the supply of programs and the creation of new Universities, Technical Formation Centers, and Professional Institutes. Graph 2.1 shows the number of students who enroll in college each year, based on the type of college they attended. The proportion of students enrolled in college who graduated from public schools has been steadily increasing in the last decade. Similarly, when we rank schools according to the proportion of poor students they serve, the same pattern is observed: Poorer schools have gained participation in higher education over the years.

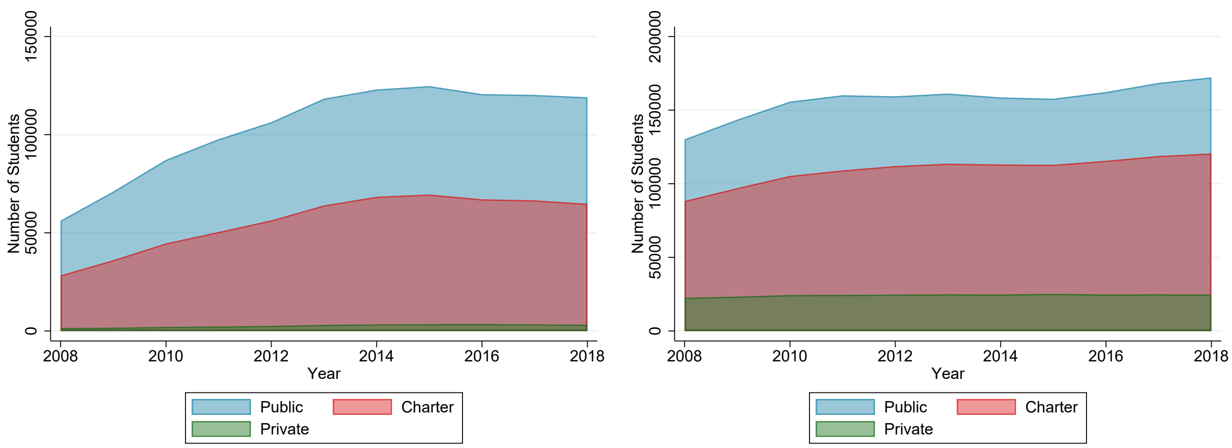
Figure 2.1: Number of Students Enrolled in Higher Education by Type of High School



Notes: County percentiles are constructed from the per capita county income. The graph only uses students who scored 600 or above in the PSU. In each bin, I show the proportion of students who enrolled in a highly selective program.

Although access for low-income students has improved over time, there are still significant barriers that determine the type of programs they choose and the quality of the institutions they attend. In graph 2.2, I redo graph 2.1 differentiating by type of program. Now, we can observe that a large part of the convergence between poor and richer students is due to an increase in enrollment in technical programs, which usually have lower returns (Espinoza and Urzua, 2015). This difference in the type of programs students choose based on their socioeconomic status invites us to ask why and how different policies can alter this trend.

Figure 2.2: Number of Students Enrolled in Higher Education by Type of High School



(a) Technical Programs (b) Academic Programs

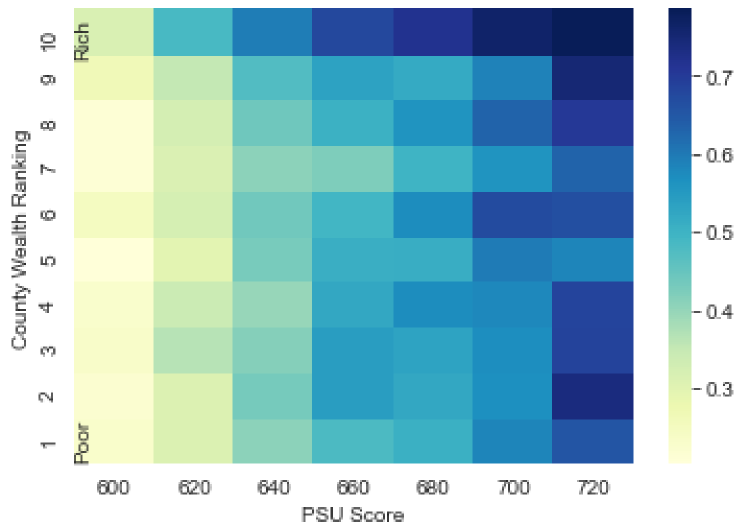
Notes: County percentiles are constructed from the per capita county income. Psu scores are groups in buns of 20 points (0.16 standard deviations). Panel a) shows students who took the PSU in 2016. Panel b) show students who took the PSU IN 2017

Part of the difference can be explained by a gap in preparation for the college admission test. Chile uses a centralized admission test called Prueba de Selección Universitaria (PSU), consisting of three parts: math, language, and Science. The final score is normalized to centered at 500 with a standard deviation of 120. Most universities use this score as the main criteria in their selection process. The other components used are high school grades and ranking, which are weighted less than the test score [1]. Students from less affluent backgrounds tend to score lower than their wealthier peers. Graph 2.3 shows the correlation between county income per capita and the average

[1]The specific weight depends on each Career and University

PSU score of the commune. The richer the county, the better the scores obtained in the PSU.

Figure 2.3: Distribution of Students Enrolling in Highly Selective Programs by County Wealth and PSU Score



Notes: County percentiles are constructed from the per capita county income. The graph only uses students who scored 600 or above in the PSU. In each bin, I show the proportion of students who enrolled in a highly selective program.

This correlation has founded the main doubts and criticisms of free-tuition programs. If it is the wealthiest students who have the greatest probability of accessing College, they would be the ones who benefit the most from free tuition. As richer students decide to attend more selective programs because of free tuition, they may end up displacing the most vulnerable students towards less selective, lower-return programs.

On the other hand, lower-income students face economic constraints that could divert them from choosing more expensive programs towards lower-risk, lower expected-returns options. As education is a risky investment, economic theory predicts that poorer, risk-averse students are less likely to invest in high-return, high-risk college programs than their richer peers, even in the absence of credit constraints and with similar expected-returns[2].

Various studies evaluating programs that increase access to credit in Chile and the United States show the existence of financial restrictions that affect students' decisions to attend higher education

[2]This is consistent with the theory of decreasing absolute risk aversion.

and the types of programs they choose (Solis, 2017; Aguirre, 2019; Bucarey, Contreras, and Munoz Henriquez, 2020). Other studies that analyze different types of monetary support for vulnerable families find similar results (Castro-Zarzur, 2018; Rosa Castro-Zarzur and Sarzosa, 2019). For example, Castro-Zarzur (2018) estimates that the Teacher's Vocation Scholarship, which granted free tuition in education programs in Chile, was successful in attracting skilled, low-income students. In the United States, similar results confirm that the most vulnerable students are more susceptible to changing their decisions when they receive monetary support.

In a related literature, Hoxby and Avery (2013) argue the existence of a gap in the matching of Universities and poor students. They find that low-income students tend to go to less selective programs even when they present the same academic performance as their more affluent peers. The authors venture to explain this gap for reasons of asymmetries of information, expectations, or economic restrictions. Regarding the latter, the state-guaranteed loan in Chile, which increased access to credit for low-income students, has managed to expand opportunities for the most vulnerable students (Solis, 2017). Nevertheless, despite having access to credits, one still wonders if there is still a gap between the program that students choose and those they should access according to their academic performance.

Graph 2.3 shows the proportion of students who attend higher education based to their PSU score and the county where they lived when they graduated from high school. The counties are ranked from poorest to richest, using county per capita income. Focusing on the cohort that took the PSU in 2014, I show how students with a similar PSU score make different decisions depending on the county they reside in. Graph 2.3 shows the proportion of students in each cell that enrolled in a highly selective program [3]. The most affluent counties located at the top of the graph are Las Condes, Vitacura, Santiago, Viña del Mar, and Providencia. Among the counties with the lowest per capita income are San Pedro de la Paz, Temuco, Puente Alto, Maipú and Lo Espejo. This graph suggests that a student who scored 640 points (about one standard deviation above the average) in one of the wealthiest counties has the same probability of enrolling in a highly selective

[3] I define selectivity based on the average PSU score of admitted students

program as a student who scored 720 points (just under two standard deviations above the mean) in a poor county. This pattern reflects a potential mismatching of students to programs and its relation to socioeconomic status. If these differences appear in the early application process, as Hoxby and Avery (2013) suggests, then free tuition could have a significant effect on access to selective programs for low-income, high-achieving students.

Furthermore, understanding the effect of free tuition on the type of programs students enroll in can have important long-term implications. For example, Zimmerman (2014) shows that returns to college admission in Florida led to a considerable return for those students who were admitted at the margin. Furthermore, the returns were higher for low-income students. In Chile, Hastings et. al. (2013) and Espinoza and Urzúa (2015) find significant heterogeneity in the returns to the different programs of study, with larger returns to more selective programs. These programs are usually more expensive and have a lower graduation rate, becoming a riskier decision for low-income students, who must cover the cost of their studies through loans. In this case, Hastings et. al. (2013) find that returns do not differ by the socioeconomic status, suggesting that policies aimed at increasing the participation of low-income students in more selective programs may have significant public policy implications.

2.3 Free Tuition Policy

Until 2016, Chile was characterized by highly private financing of higher education, government support took the form of scholarships and subsidies with a merit component, imposing specific performance requirements to access such subsidies. Perhaps the most notorious and widespread financial aid is the state-guaranteed loan program, which, although not a subsidy per-se, did allow many students to access loans in order to finance college (Solis, 2017). Eligible students tend to forgo technical education to enroll in academic programs, which tend to be longer and more expensive (Aguirre, 2019; Bucarey, Contreras, and Munoz Henriquez, 2020). This, coupled with a decline in the graduation rate, has led several politicians and economists to raise doubts about the long-term effects of student loans.

With the introduction of free tuition in 2016, Chile moved towards a more significant public financing of higher education, where financial support depends on the economic needs of families and no longer on the student's academic performance. In its first year of implementation, this policy benefited students who belonged to the poorest 50% and enrolled in one of the Universities that ascribed to the policy. Initially, only public universities, and some private universities, were eligible for free, which left out Professional Institutes (PI) and Technical Formation Centers (CFT), focusing mainly on technical education.

In 2017, free tuition was extended to IP and CFTs, allowing students to enroll in technical programs. In total, 30 universities were part of this policy in the first year, which expanded to 44 in the second year when technical education was included.

The policy finances 100% of the cost of the program for a period equivalent to the duration of the program. Five years for academic programs, and between 2 and 4 years for technical or academic programs not leading to an bachelors degree. On average, a student studying an academic program will receive a subsidy close to $ 30,000 over the five years of the degree.

One of the most common criticisms o this policy is the high cost it represents for the state. In 2018, the cost of free tuition was close to 1,500 $US. With this, Chile ranks as one of the countries that spend the most on higher education, relative to the other levels of education (Espinoza and Urzúa, 2015). This has led many experts to focus on the opportunity cost of this policy.

Beyond the total cost that a free-tuition policy may represent, the bigger problem, according to many experts and politicians, is the distributional cost that it may imply. Free tuition could negatively affect low-income students by encouraging their more affluent peers, who tend to obtain better scores in the PSU, to enroll in free programs. Therefore, they would displace poorer students who, without this increase in the demand, would have accessed such programs (Bernasconi, 2019; Gayardon and Bernasconi, 2016; Bucarey, 2018).

Until today, few studies analyze the effects of free access to higher education for vulnerable students. Torres-Cortes (2019) uses a multilevel estimation to estimate that eligible students changed their applications to more selective and expensive programs. Similarly, Rosa Castro-Zarzur and

Sarzosa (2019), using a difference-in-difference approach, estimates that the introduction of free tuition caused low-income and high-performance students to reduce their application to education programs (which were already free for eligible students because of the Teacher's Vocation Scholarship) towards more selective careers and with a greater expected return. Finally, Bucarey (2018) uses a structural model to estimate the effect of universal free education on access to higher education for low-income students. Bucarey (2018) suggests that those students who would have accessed selective programs through targeted scholarships will now be displaced towards less selective programs in a scenario of universal free tuition.

2.3.1 Who benefits from free tuition?

As argued above, one of the main concerns of free tuition is that it may harm the poorest students, increasing inequality in access to higher education. Table 2.1 shows descriptive statistics of the students who benefited from free education in 2016 and 2017. Most of them come from public schools, they are considered a priority by the Ministry of Education, and they are more likely to be first-generation students. At the same time, 23% of the students who enrolled in higher education for free graduated in the top 10% of their high school cohort. For students who enrolled without free tuition, this percentage was 14%.

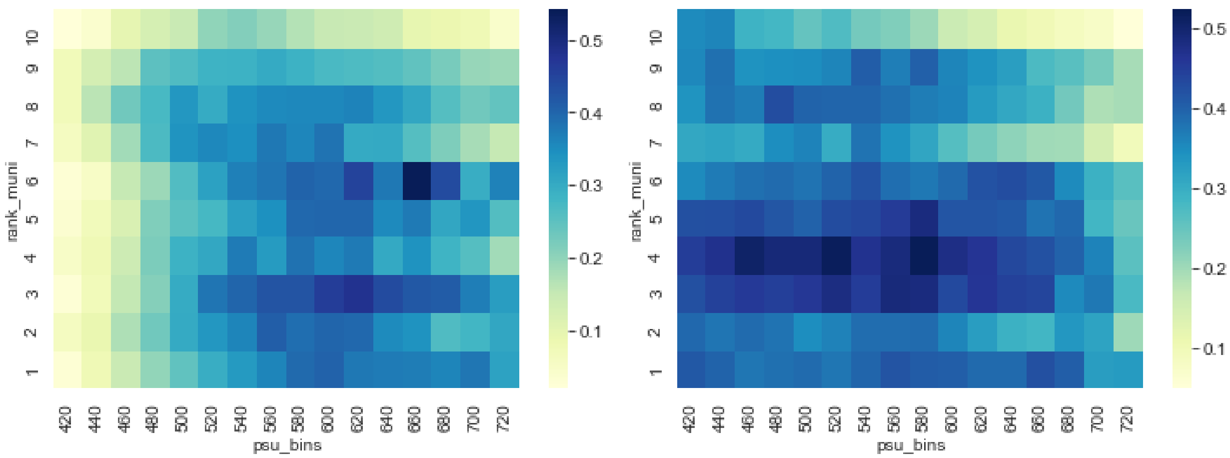
On the other hand, students who benefit from free tuition tend to come from vulnerable counties but not from the poorest ones. Graph 2.4 shows the correlation between the wealth of the county and the percentage of students who accessed the free education. In 2016, when technical education was not covered by the policy, most beneficiaries lived in medium- to low-income counties and obtained a PSU score above the average. In 2017, when technical education was included, although the representation of counties did not vary considerably, the proportion of students who had poorer results in the PSU did increase.

Table 2.1: Characteristics of Students Receiving Free Tuition

	Free Tuition (1)	Paid Tuition (2)
Female	0.50	0.51
Priority Student	0.72	0.38
Parents with Higher Ed.	0.08	0.12
Type of School		
Public	0.39	0.30
Subsidized	0.55	0.52
Private	0.02	0.14
Technical High School	0.31	0.25
Student Performance		
Top 10%	0.23	0.14
Decile 2	0.15	0.11
Decile 3	0.12	0.11
Decile 4	0.11	0.11
Decile 5	0.09	0.10
Decile 6	0.08	0.10
Decile 7	0.07	0.09
Decile 8	0.06	0.09
Decile 9	0.05	0.08
Decile 10	0.03	0.06
N	77,915	555,394

Notes: Sample is composed by all student enrolled in higher education in 2016 or 2017. I split the sample into two columns. Column (1) uses all beneficiaries of free tuition. In Column (2), the universe is those students who enrolled in higher education without free tuition.

Figure 2.4: Distribution of Students Receiving Free Tuition by County Wealth and PSU Score



(a) 2016 (b) 2017

Notes: County percentiles are constructed from the per capita county income. Psu scores are groups in buns of 20 points (0.16 standard deviations). Panel a) shows students who took the PSU in 2016. Panel b) show students who took the PSU IN 2017

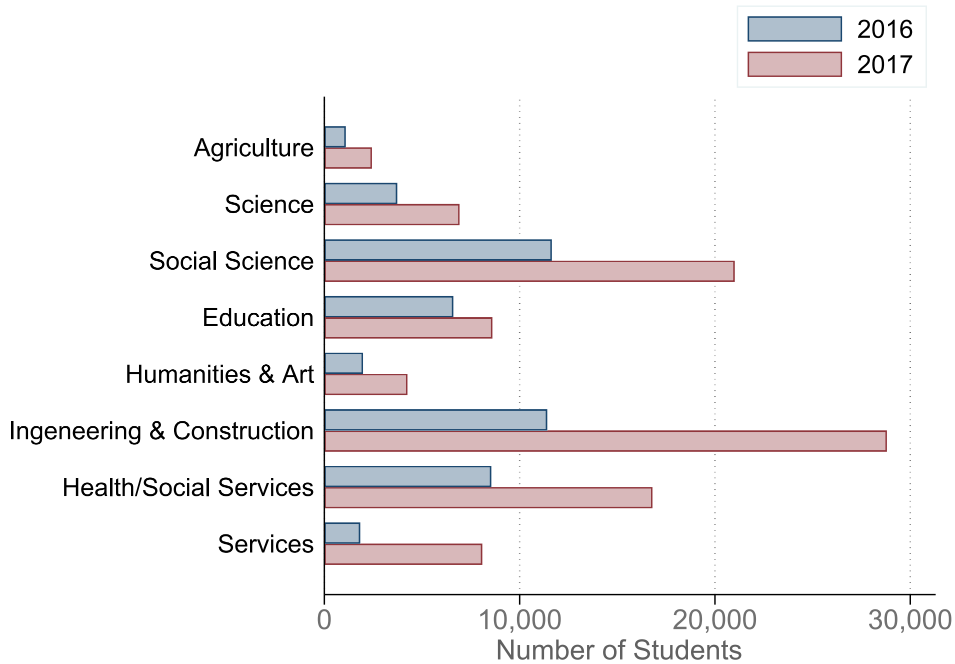
When we do a ranking of schools based on the proportion of poor students they serve, we see that most of the beneficiaries do not come from the most vulnerable schools but from those in the middle of the distribution. Together, this shows that, although beneficiaries do come from vulnerable backgrounds, the most disadvantaged ones use this benefit to a lesser extent.

2.3.2 Where do they go?

Another point of discussion about free tuition refers to the type of programs that beneficiaries access. As low-income students have a disadvantaged when taking the college admission test, we would expect that they will tend to enroll in less selective programs with lower economic returns. On the other hand, if there are economic barriers in their decisions, then many of them will choose to enroll in more selective programs.

Graph 2.5 shows the most common study areas among students who entered the year 2016 and 2017 to study for free. In both years, most of the students focused on social studies or engineering and construction. The notable increase in 2017 in the engineering area is due to the incorporation of technical careers in the construction sector.

Figure 2.5: Most Common Areas of Study Among Students Receiving Free Tuition



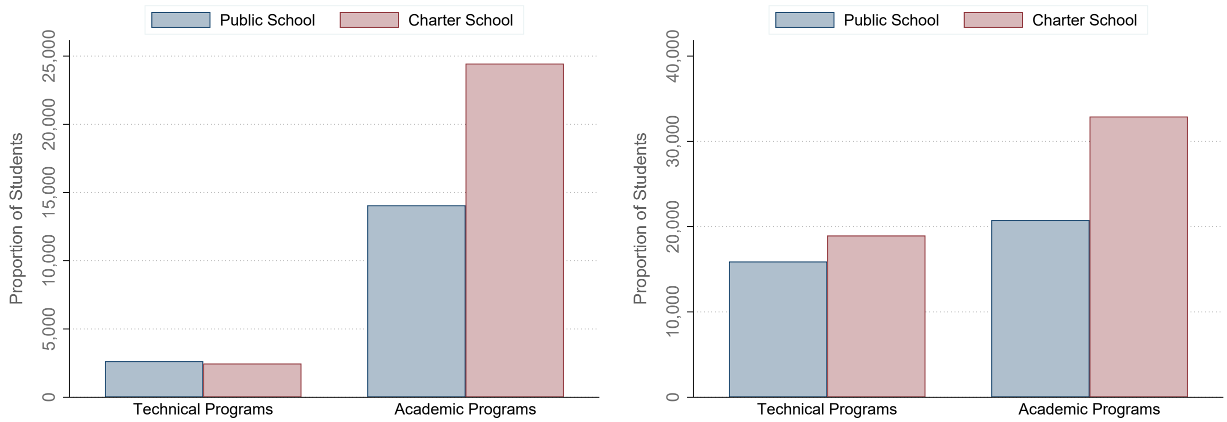
Notes: I use every student who enrolled in college in 2016 and 2017.

For 2016 and 2017, the five most common programs among beneficiaries are Business, Law, Industrial Engineering, Nursing, and Journalism. These are usually high-return programs.

Consistent with this, beneficiaries enrolled to a greater extent in highly selective professional programs. In 2016, about 20% of the students with free tuition entered a program within the top 10%. Among the students who enrolled without free tuition, only 9% entered these programs. Nevertheless, there is also a considerable increase in students entering less selective programs when the policy included technical education, in 2017.

Graph 2.6 shows that while the majority of students enrolled in academic programs, students in public schools are more likely to enroll in technical education compared to their peers in charter schools. Similarly, graph 2.7 shows that charter school students tend to enroll more in more selective programs, suggesting that even in the absence of economic constraints, there is still significant heterogeneity according to the student's socioeconomic level.

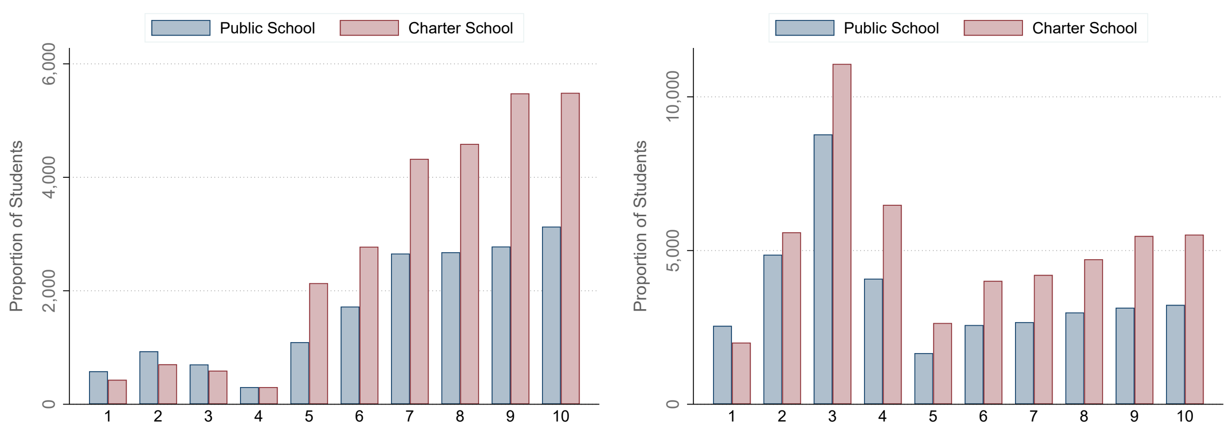
Figure 2.6: Distribution of Students Receiving Free Tuition by County Wealth and PSU Score



(a) 2016 (b) 2017

Notes: I use every student ho enrolled in college in 2016 and 2017 for whom I had high school information.

Figure 2.7: Number of Students Enrolling in College by Program Ranking and Type of High School



(a) 2016 (b) 2017

Notes: I use every student who enrolled in college in 2016 and 2017 for whom I had high school information.

2.4 Conclusion

Despite the progress that Chile has made in access to higher education, there are still various barriers that affect the probability of a low-income student accessing selective programs with high economic returns. For example, in 2014, even with access to state-endorsed credit, a student living among the poorest counties had a considerably lower probability of attending a selective program compared to students in more affluent counties. Furthermore, a wealthy student whose score was one standard deviation above average was just as likely to attend a top 10 program as a poor student whose score was almost two standard deviations above average. This gap is what Hoxby and Bulman (2016) call the mismatch of low-income students to program quality.

This mismatch has critical economic implications due to the heterogeneity in the returns of each type of program. As seen, the programs with the highest returns tend to be more expensive and risky since they have a higher level of difficulty. This uncertainty in the expected returns is one factor determining the mismatch between low-income students and selective programs. By removing part of the risk, free tuition allows low-income students to attend programs they previously dismissed for economic reasons.

Most of the beneficiaries of the free tuition policy come from what we could call the middle class. They are students who have relatively high high school performance compared to their classmates. They are more likely to be considered "priority students" and have less educated parents than the average college student in Chile. Nevertheless, the most vulnerable students use this benefit to a lesser extent than their more affluent peers. For example, charter school graduates are more likely to attend academic programs than those from public schools. At the same time, the most vulnerable schools have a lower representation among beneficiaries, suggesting that the lower tail of the distribution benefits less than those in the middle.

All this suggests that there is still a gap in academic performance among students from schools with different degrees of vulnerability. Therefore, alternative and complementary policies are required to reduce the educational inequalities they face when deciding to enroll in higher education.

Finally, we find that the beneficiaries do not have a greater probability of dropping out of college in the first three years of their studies, which we would expect because they are usually students with good school performance. This evidence again suggests that tuition can reduce the mismatch between low-income students and quality programs.

Appendices

Appendix A. Robustness Check and Alternative Strategies

Appendix A.1. Alternative difference-in-difference approach

I first estimate an alternative model that overcomes the self-selection issue, while avoiding behavioral assumptions, by using all students who finished high school, instead of just those who applied for financial aid. This means I cannot use eligibility status. So, I ranked schools based on the proportion of priority (poor) students and compare enrollment changes between students in poor schools to students in the richest schools, as described in section 3.2.2.

Table A1 presents the results of the Difference-in-Difference estimation using this school-level variation. Students in poorer schools were more likely to enroll in college after the policy, compared to the change in the top school-decile. This was driven predominantly by an increase in academic programs. Low-income students were 7.1-7.6 percentage points more likely to enroll in an academic program, which represents a 57% increase, and 1.7-3.2 percentage points more likely to enroll in a technical program, an 8-15% increase. The net effect on technical enrollment quickly gets to statistical zero after the second decile. This is also shown graphically in Figure A1, which plots the coefficient of interest for each school decile in the 2016 cohort. Academic programs present similar trends, although somewhat smoother, reaching statistical zero at the eighth decile.

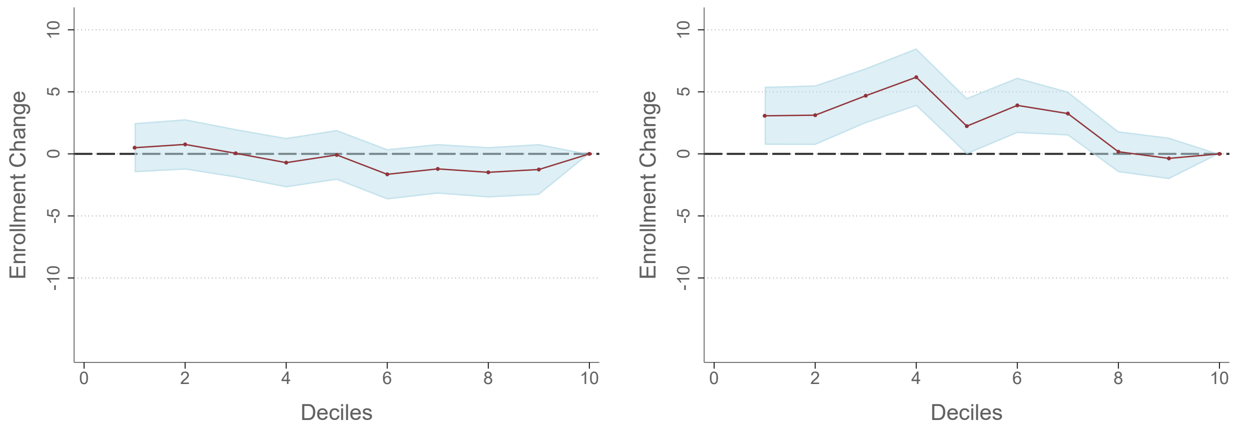
Table A1: Difference-in-difference Using School Priority Deciles

	Decile 1	**Decile 2**	**Decile 3**	**Decile 4**	**Decile 5**	**Decile 6**	**Decile 7**	**Decile 8**	**Decile 9**
A. 2016 High School Cohort									
No College	-0.088***	-0.108***	-0.092***	-0.086***	-0.060***	-0.047***	-0.035***	0.003	0.002
	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)	(0.014)	(0.012)	(0.011)	(0.011)
Technical Program	0.017*	0.032***	0.012	0.010	0.017	0.002	0.006	-0.006	0.003
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Academic Program	0.071***	0.076***	0.079***	0.076***	0.043***	0.045***	0.029***	0.004	-0.006
	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.013)	(0.010)	(0.009)	(0.009)
B. 2015 High School Cohort									
No College	-0.036***	-0.039***	-0.047***	-0.055***	-0.022*	-0.023*	-0.020*	0.013	0.016
	(0.0130)	(0.0136)	(0.0132)	(0.0135)	(0.0129)	(0.0128)	(0.0115)	(0.0112)	(0.0113)
Technical Program	0.005	0.008	0.005	-0.007	-0.001	-0.017	-0.012	-0.015	-0.013
	(0.0101)	(0.0104)	(0.00997)	(0.0102)	(0.0103)	(0.0104)	(0.0102)	(0.0104)	(0.0105)
Academic Program	0.031**	0.0312**	0.0469***	0.0618***	0.0223*	0.0391***	0.0325***	0.00173	-0.00363
	(0.0119)	(0.0123)	(0.0113)	(0.0119)	(0.0116)	(0.0114)	(0.00905)	(0.00843)	(0.00854)
2014 Mean									

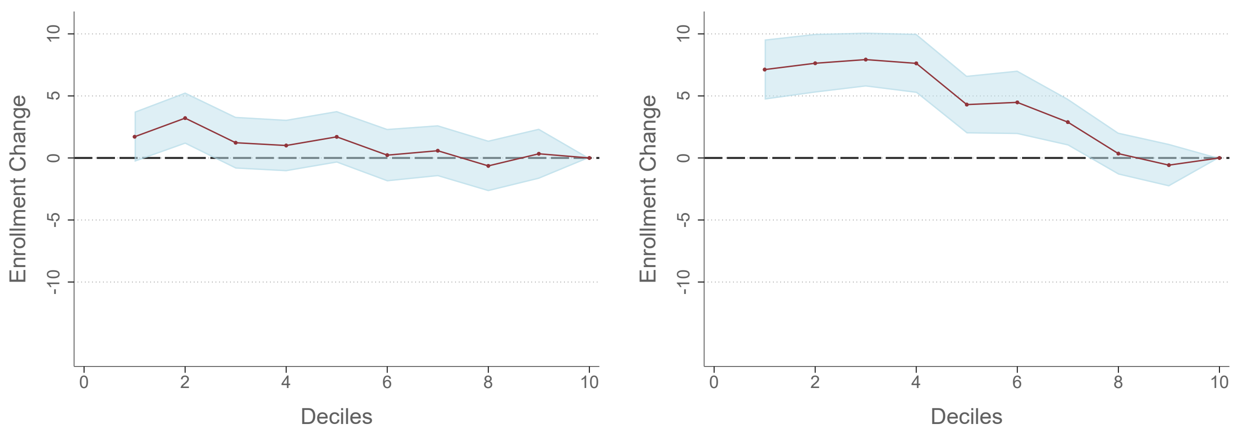
Note: High school deciles are constructed from a ranking of high schools based on the proportion of poor students that attend there. Poorer schools (i.e., those with a higher proportion of poor students) are in the lower deciles. The higher the percentile, the richer the school. Panel A shows the results for cohort 2016 and panel B shows the results for cohort 2015. I use decile 10 as the baseline comparison group and cohort 2014 as the baseline cohort.
Standard errors, in parentheses, are clustered at the school level.
*** p<0.01, ** p<0.05, * p<0.1

Figure A1: Effect of Free Tuition by High School Priority-Decile

2015 High School Cohort



2016 High School Cohort



(a) Technical Program (b) Academic Program

Notes: Each point represents the coefficient of the interaction between the cohort fixed effect and the school priority decile. The shaded area represents the 95% confidence interval. Schools in lower deciles are schools with a larger proportion of priority students (i.e., poorer schools). The first column shows the effect of free tuition on enrollment in technical programs, the second column on enrollment in academic programs. Each row shows the results for specific high school cohorts. All these estimates come from a multinomial logit model where I use cohort 2014 as the baseline cohort and school decile 10 as the baseline decile.

Because the variation comes at the school level, this procedure yields noisier estimates. It is also important to notice that the interpretation of these coefficients is slightly different than for the main strategy. Here, instead of comparing eligible to non-eligible students, we are comparing students in poor schools to students in the richest schools.

Results are consistent with the presence of heterogeneous effects, where low-income students were more likely to react to free-tuition by enrolling, mostly, in academic programs. Also, consistent with results from the selection model, I find that lower-income students were more likely to move from no-college to technical programs, compared to richer eligible students, who moved mostly to academic programs.

Appendix A.2. Robustness checks

Table A2 shows the results using different specifications. In Panel A, I use a simple multinomial logit model with no self-selection correction. By not correcting for self-selection, we overestimate the effect of the policy in this case. Because there are two different forces biasing the results in opposite directions, the resulting bias is moderate, but statistically different from zero. On one hand, students who could correctly predict their eligibility status were more likely to fill the FUAS after the policy. These new applicants are more price-sensitive and more likely to expect lower returns from higher education. This group biases the results downwards. On the other hand, marginally non-eligible students, who filled the FUAS for the chance of free tuition, ended up not enrolling when eligibility status was disclosed. This group upward biases the estimation. Results in Panel A) suggest that the latter effect was stronger.

In Panel B, I use "priority student" as a proxy for being eligible. This is, I estimate the model with measurement error. Because many eligible students are not priority students, we may expect downward bias from this misclassification[4]. Priority students were 4.7 percentage points more likely to attend academic programs because of free tuition. This may be interpreted as a lower-bound of the effect.

Finally, the last three panels use different numbers of nodes to approximate the distribution of the unobserved factor. Results are not statistically different from the main specification. This suggest that using four nodes is a good approximation of the actual distribution of the unobserved heterogeneity.

[4]This is not attenuation bias due to classical measurement error, because the misclassification here is not classical in the sense that priority students are more likely to be eligible. This means the error is likely positive.

Table A2: The Effect of Free Tuition on College Choice. Difference-in-Difference Robustness Check

	No college	Technical Program	Academic Program
A. Eligible - no selection correction			
Eligible × C_{2015}	-0.044***	-0.017***	0.061***
	(0.004)	(0.004)	(0.004)
Eligible × C_{2016}	-0.078***	-0.003	0.081***
	(0.004)	(0.004)	(0.004)
	0.100		
B. Priority Students			
Priority × C_{2015}	-0.0211***	-0.00336	0.0244***
	(0.00307)	(0.00237)	(0.00284)
Priority × C_{2016}	-0.0504***	0.00350	0.0469***
	(0.00308)	(0.00237)	(0.00284)
	0.1131		
C. Selection Corrected - 4 types			
Eligible × C_{2015}	-0.0397***	-0.00936***	0.0490***
	(0.00358)	(0.00305)	(0.00388)
Eligible × C_{2016}	-0.0732	0.00469	0.0685***
	(0.00358)	(0.00307)	(0.00390)
D. Selection Corrected - 6 types			
Eligible × C_{2015}	-0.0398***	-0.00951***	0.0493***
	(0.00340)	(0.00284)	-0.00381
Eligible × C_{2016}	-0.0746***	0.00493*	0.0697***
	(0.00341)	(0.00286)	(0.00383)
E. Selection Corrected - 8 types			
Eligible × C_{2015}	-0.0407***	-0.00885***	0.0495***
	(0.00337)	(0.00286)	(0.00370)
Eligible × C_{2016}	-0.0766***	0.00643**	0.0701***
	(0.00338)	(0.00288)	(0.00372)

Note: Coefficients for the interaction of the treatment variable and cohort are shown. All panels, but panel B, uses eligibility as the treatment variable. Panel A shows the result for a naïve multinomial logit, where no correction for self-selection was in place. Panel B) uses the priority student indicator as the treatment variable, as a proxy for eligibility. Panel C-E show the result for the selection model, varying the number of nodes used to approximate the distribution of the unobserved factor. Standard errors, in parenthesis, are obtained from a bootstrap procedure.
*** p<0.01, ** p<0.05, * p<0.1

Appendix B. Likelihood Function and EM Algorithm

Given that students choose to apply for financial aid and to attend college, the contribution to the likelihood function of student i can be written as

$$
\begin{aligned}
L_c(\Theta|\eta) = & \left[Pr(FUAS=1|\eta)\Pi_{j=1}^{J} Pr(c=j|\eta)^{\mathbf{1}(c=j)}\right]^{\mathbf{1}(FUAS=1)} \\
& \times Pr(FUAS=0|\eta)^{\mathbf{1}(FUAS=0)}
\end{aligned}
$$

Where $FUAS$ is an indicator function of whether the student filled the FUAS, and c describes the college choice. The unobserved heterogeneity, η, is modelled to capture the correlation between financial aid and college decisions. By integrating out this unobserved heterogeneity, we get the unconditional likelihood function.

$$
\begin{aligned}
L_c(\Theta,\eta) = & \int_{\eta} \left[Pr(FUAS=1|\eta)\Pi_{j=1}^{J} Pr(c=j|\eta)^{\mathbf{1}(c=j)}\right]^{\mathbf{1}(FUAS=1)} \\
& \times Pr(FUAS=0|\eta)^{\mathbf{1}(FUAS=0)} dF(\eta)
\end{aligned} \tag{2.1}
$$

One common way to do this is to assume a functional form for the unobserved factor, usually a normal distribution, and numerically integrate equation 2.1. In a Discrete Factor Maximum Likelihood procedure, instead of assuming a functional form, we approximate the distribution with mass points η_k, with $k=1,...,K$. The unconditional likelihood function in this case is

$$
\begin{aligned}
L_c(\Theta,\eta) = & \sum_{k=1}^{K} p_k \left[Pr(FUAS=1|\eta_k)\Pi_{j=1}^{J} Pr(c=j|\eta_k)^{\mathbf{1}(c=j)}\right]^{\mathbf{1}(FUAS=1)} \\
& \times Pr(FUAS=0|\eta_k)^{\mathbf{1}(FUAS=0)}
\end{aligned} \tag{2.2}
$$

Where p_k is the probability of the student of being in the mass point η_k. This procedure is equivalent to a latent class model, where each mass point represents a type of student.

Using an Expectation-Maximization algorithm significantly simplifies the estimation of this likelihood function. Because college choice is independent of financial aid application, conditional on the unobserved factor, we can estimate both equations – college choice and FUAS application

– separately once we control for the unobserved factor.

The general procedure of the EM algorithm is as follows:

1) Set initial values for the parameters by fitting a multinomial logit model, with no correction for self-selection, for the college choice equation, and a logit model for the FUAS application equation. Each student is given the same probability of being of each type, $1/K$, where K is the number of types.

2) Calculate the likelihood in 2.2 using the parameters in step 1.

3) **Expectation step**: Update the probability of being type k, by

$$Pr(k)'_i = \frac{S_k \times L_{ic}(\Theta|\eta_k)}{\sum_{k=1}^{K} S_k \times L_{ic}(\Theta|\eta_k)}$$

Where $S_k = \frac{1}{N}\sum_{i=1}^{N} Pr(k)_i$, is the share of students of type k in the previous iteration.

4) **Maximization step**: Estimate the probability of filling the FUAS, weighting each observation[5] by the probability of being of each type. Similarly, estimate the college choice equation, conditional on filling the FUAS, using a multinomial logit weighted by the probability of being of each type.

5) Calculate the likelihood function given these new parameters.

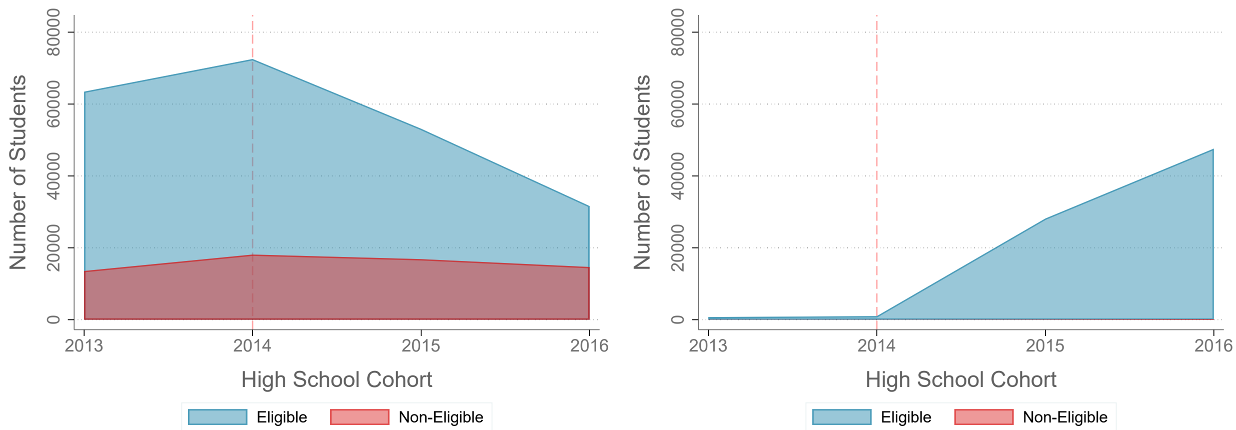
6) Repeat steps 3 - 5 until convergence.

For the main results, convergence is obtained when the difference between the average likelihood functions is less than 0.000001. Nevertheless, I define more stringent criteria of convergence as robustness check and, although the number of iterations needed for convergence increased significantly, results did not significantly change. Figure **??** shows the convergence path for the likelihood function.

[5]Each student here is duplicated k times, so each observation is a student/type combination

Appendix C. Tables and Figures

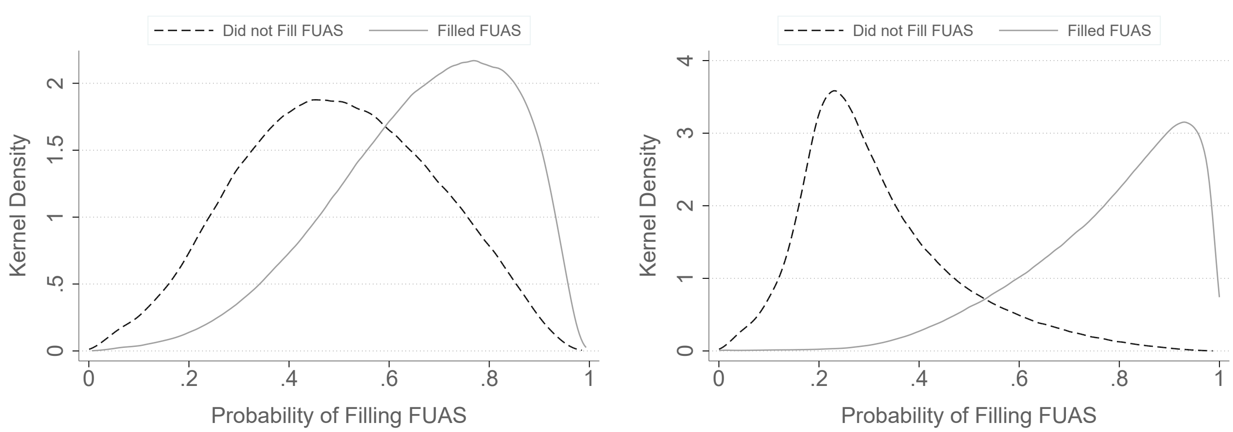
Figure C1: Number of Students Receiving Financial Aid



(a) Other Financial Aid (b) Free Tuition

Note: Number of students receiving some kind of financial aid in each cohort the year they graduated from high school. In 2014, almost 70,000 thousand students received financial aid. Of those, 18,000 thousand were above the 50% cutoff for free-tuition, while 52,000 students were among the poorest 50% of the population.

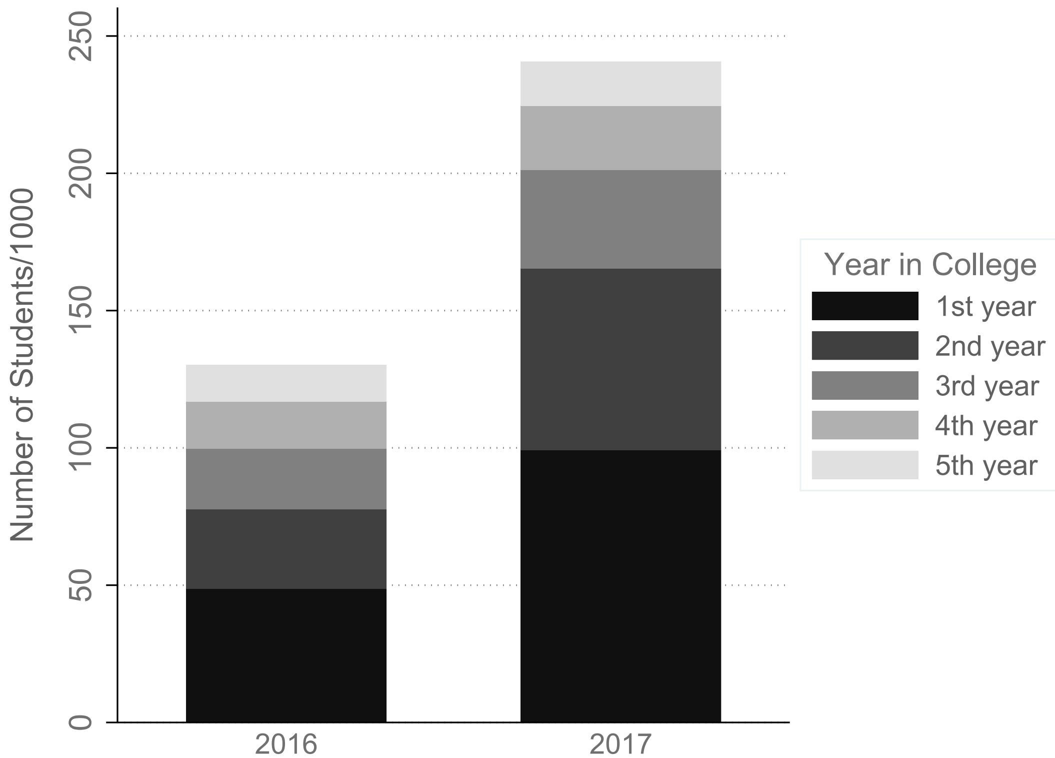
Figure C2: Predicted Probability of Filling FUAS, by FUAS Status



(a) Without Unobserved Heterogeneity (b) With Unobserved Heterogeneity

Notes: Panel (a) show the predicted probability of filling the FUAS from a Probit model where the dependent variable was whether the student filled the FUAS or not. Panel (b) plots the predicted probability from the full selection model, which includes the unobserved heterogeneity. The unobserved factor dramatically increases the ability of the model to predict financial aid application.

Figure C3: Distribution of Students with Free Tuition by Year in College



Notes: For each academic year, the hight of the bar represents the total number of students receiving free tuition. In 2017, as new institutions adscribed to the policy and technical programs were included, we see a significant increase in the number of students receiving free tuition who enroll in college for the first time. The avergae academic program in Chile lasts 5 years, while technical programs last between 2 to 4 years.

Table C1: Higher Education Institutions Ascribed in Free-Tuition Policy

University	PI	CTF
Since 2016		
Católica de Chile		
Católica de Valparaíso		
Alberto Hurtado		
de Antofagasta		
Arturo Prat		
Austral		
Autónoma		
del Bío Bío		
Católica C. Silva Henríquez		
Católica de la S. Concepción		
Católica de Temuco		
Católica del Maule		
Católica del Norte		
de Concepción		
de Atacama		
de Chile		
de Santiago de Chile		
de Talca		
Diego Portales		
Técnica Federico Santa María		
Finis Terrae		
de la Frontera		
de La Serena		
de Los Lagos		
de Magallanes		
M. de Ciencias de la Educación		
de Playa Ancha		
de Tarapacá		
Tecnológica Metropolitana		
de Valparaíso		
Since 2017		
Universidad de Aysén	IP Adolfo Matthei	CFT CEDUC UCN
Universidad de O'Higgins	IP Arcos	CFT de Tarapacá
	IP de Chile	CFT DUOC UC
	IPl DUOC UC	CFT ENAC
	IP INACAP	CFT INACAP
	Inst. Nacional del Fútbol	CFT San Agustín de Talca

Table C2: Proportion of Eligible Students by High School Priority Deciles

	Cohort					
	2014		2015		2016	
School Decile	Eligible (%)	Priority (%)	Eligible (%)	Priority (%)	Eligible (%)	Priority (%)
1	90.5	83.4	87.0	75.2	88.1	76.7
2	86.3	72.4	82.4	64.1	82.1	65.7
3	83.5	65.8	77.7	57.4	79.1	59.4
4	79.7	59.9	75.1	51.8	76.4	53.8
5	76.3	54.0	72.2	47.0	73.9	49.0
6	71.4	47.9	67.9	41.3	68.8	43.3
7	62.6	40.2	61.6	35.0	62.3	36.8
8	51.2	29.2	52.4	25.8	52.5	27.9
9	35.0	16.6	39.1	14.8	37.0	16.7
10	13.9	2.7	22.0	2.4	11.7	2.7

Note: This table shows the variation in eligibility status based on how poor is the school. High school deciles are constructed from a ranking of high schools based on the proportion of poor students that attend there. Poorer schools (i.e., those with a higher proportion of poor students) are in the lower deciles. The higher the percentile, the richer the school.

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Vita

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