Who Pays for Free College? Crowding Out on Campus*

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Abstract

Free college tuition has been central in the higher education policy debate. In Chile, a government elected in 2014 promised free university tuition by 2020. Most research on tuition subsidies focuses on enrollment gains for newly eligible students. This paper studies spillover of these policies to students currently receiving generous financial aid. I show that free tuition increases demand at selective programs, making these programs more competitive and pushing them out of reach for many low-income students who would have qualified otherwise. The argument uses a combination of reduced-form regression-discontinuity estimates of enrollment elasticities and a structural model that captures general equilibrium effects. Estimates using Chilean administrative records suggest that 20% of currently enrolled poor students will lose seats to wealthier students under a free-tuition policy. This adverse effect on low-income students could be mitigated by complementary policies such as capacity investments and means-testing. However, crowd-out remains significant unless aggressive policies to counteract it are enacted.

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1 Introduction

Making college tuition free for all has been at the center of policy debates in several countries and states. For example, Chilean students have protested since 2011, demanding that higher education become more affordable. In 2014, Chileans elected a new government that promised to make college free for everyone by 2020 (Bachelet, 2012). This is also a contentious issue in other countries, and in each of these contexts, advocates argue free college would expand access to higher education for groups left behind by financial aid policies (Clinton, 2015; Sanders, 2015).[1]

This debate has largely ignored the potential negative consequences that free college tuition might pose for low-income students who already have access to higher education as a result of financial aid. An across-the-board reduction in college costs may cause middle- and upper-income students to apply to colleges that are more expensive. At selective institutions, these new applicants might end up crowding out low-income students, who on average have lower test scores.

The equilibrium effects of free college on admissions and its distributive impact depend mainly on three factors: the change in preferences over college alternatives, the distribution of admission test scores and income among students, and the socio-economic composition of students who are at the margin of admission. Because prices do not clear the market, programs that face an excess demand will therefore need to become more selective in their admissions. In equilibrium, students who are crowded out are either directly displaced by new beneficiaries of financial aid who changed their applications or displaced by the previous group after they try to enroll elsewhere, starting a chain of displacement. It is challenging to study the phenomenon of crowding out because free college affects the whole market.

In this paper, I use rich administrative data from Chile to study the access to higher education for low-income students under free tuition and the design of financial aid policies. College students in Chile are directly admitted into a specific college-major, and admission depends exclusively on a weighted average score of a national admission test and students' high school GPA. Each college-major admits the best applicants according to a score, generating a transparent channel for crowd-out: a more qualified student can displace students in the admission process. Additionally, financial aid is awarded based on sharp eligibility rules on income and test scores. Finally, financial aid expansions that took place since 2012

[1] Countries where this has been a topic of discussion in recent years include Chile, England, Germany, and the United States. In the US, the states of Florida, Maryland, New Jersey, Ohio, Washington, and Wisconsin have introduced proposals to make tuition free for all, while other states and cities have already implemented free tuition policies, including Chicago, Illinois; Detroit, Michigan; New York; Oregon; Rhode Island; San Francisco, California; and Tennessee.

provide the opportunity to study whether low-income students were crowded out.

The argument is developed in three parts. First, I test whether low-income students were crowded out by using past expansions in financial aid eligibility. Until 2011, eligibility for government scholarships was restricted to students in the first two income quintiles, and starting in 2012, it expanded to cover students in the third income quintile. I use this change in a difference in differences strategy and compare college-majors with different shares of students with a scholarship in the pre-expansion period as a proxy to where new beneficiaries would apply. I find that programs with a one standard deviation higher share of low-income students in the pre-expansion period experienced an increase in admission cutoffs of 0.7 standard deviations and a 10% drop in their share of low-income students after financial aid expanded. However, the causal interpretation of these results is complicated by the equilibrium nature of the problem. Students who are crowded out might displace others when applying to their next-favorite alternative. This propagation has the potential of affecting all programs and control groups. For this reason, and in order to study the distributive implications of free college and the importance of its design, my main empirical strategy directly addresses these forces.

Second, I build and estimate an equilibrium model of the college market. The model allows me to determine how demand changes with free tuition, how selectivity would need to increase in order to clear the excess demand, and who is crowded out in equilibrium. To build and estimate the model, I leverage the existence of a large centralized admission system and the discontinuous eligibility for scholarships. The centralized admission system in Chile uses a version of the deferred-acceptance algorithm that creates a stable match between students and colleges.[2] Stability implies that everyone chooses their favorite program within their choice set, and I use this to estimate a standard random utility model that allows me to determine each student's ordering of college-majors under different financial aid policies. Additionally, knowing the rules used in the admissions process simplifies finding the new match under free tuition.

The key parameter of the demand model, the sensitivity to prices, is estimated using a regression discontinuity (RD) design on scholarship eligibility. The RD provides local but large quasi-experimental variation in tuition that helps to identify the key parameter for the free tuition counterfactual and solves the price endogeneity problem of demand estimation. Building on Berry and Haile (2014), I prove that the RD non-parametrically identifies price response for a general class of preference models. Additionally, reduced form RD analysis reveals that scholarship eligibility increases enrollment by 6 percentage points and motivates students to substitute away from non-eligible programs. This is in line with a growing quasi-

[2]The centralized admission system enrolled 76% of new high school graduates in 2015.

experimental literature on the effects of financial aid for newly eligible students in different countries and regions (e.g. Goodman (2008), Cohodes and Goodman (2014), Angrist et al. (2014), Goldrick-Rab et al. (2016), and Solis (2017)).

Third, my equilibrium analysis shows that when college is free but capacity is unchanged, low-income students are crowded out. They are hurt because middle-income students would apply to more selective and expensive colleges, displacing low-income students. Indeed, my demand estimates show that under baseline admission cutoffs, free tuition would create an excess demand of 36%. In absence of prices, this market adjusts any excess demand by increasing selectivity; this increase disproportionately affects low-income students, who are more likely to be the least qualified admitted students. I estimate that around 13% of students in the poorest 40% of the population would be displaced from programs at the centralized assignment system, and around 5% of them would end up unassigned after free tuition is introduced. Consequently, the policy has a negative welfare effect on low-income students, with losses ranging between 3 and 6 thousand dollars, while producing small gains between 0 and 1.5 thousand dollars for high-income students. The scenario where college is free and holding capacity is fixed is a relevant short-run benchmark because capacity expansions might be costly, and this policy mirrors the proposed government plans in Chile and elsewhere.

Finally, in practice, efforts to expand financial aid might be accompanied by colleges capacity expansions or more elaborate means-testing schemes. I therefore analyze these quantity and price instruments to determine what is needed to avoid crowding out low-income students. I show that college capacities need to increase by 10% to maintain the enrollment rate of low-income students at baseline levels. For colleges participating in the centralized system, this expansion would be twice as large as the growth experienced in the last decade. Moreover, colleges need to expand their seats by more than 20% to ensure free college does not hurt a single low-income student. This is similar to the total expansion in enrollment in the last decade among all universities, but it is unseen among the more traditional and prestigious programs at the centralized system. Alternatively, to preserve low-income students' enrollment rate while holding capacities fixed, the government would need to means-test scholarships, with the poorest 20% receiving a full scholarship and a decrease in the amount of the benefit with income, up to a scholarship of 50% for the wealthiest 20%.

Chile is an ideal setting to study my questions for several reasons. First, there is a centralized assignment mechanism that matches students to their favorite college-major using a mechanism based on Gale and Shapley's (1962) student proposing deferred acceptance algorithm, which produces a stable outcome. Further, selective universities outside the

centralized system base their admissions only on GPA and test scores. Second, there are rich administrative micro data for the whole higher education system, financial aid and, national test scores. Finally, like other countries, the issue of free college and expanding financial aid has been at the top of the policy agenda for many years.

My study relates to several strands of the literature. Bound and Turner (2007) document crowding out in the context of larger cohorts in the US. Their focus is on the lack of capacity expansions among colleges caused by reduced non-tuition resources per student. Murphy, Scott-Clayton, and Wyness (2017a, 2017b) provide descriptive evidence that low-income students may have been hurt by increased competition during England's free tuition era. These articles do not decompose resorting of students and the distributive consequences of crowding out, which is my focus. My empirical analysis aligns with research on the role of prices and quantities in centralized matching markets (Agarwal (2015, 2017)) rather than demand itself or the assignment mechanism (e.g. Hastings et al. (2009), He (2012), Agarwal and Somaini (2014), Fack et al. (2017), Abdulkadiroglu et al. (2017), Kapor et al. (2017)). Studies of financial aid such as those by Cohodes and Goodman (2014) or Angrist et al. (2017) primarily focus on identifying the price effects of college,[3] while my study uses this idea as a foundation for an equilibrium analysis. Other work such as Kapor (2016), Fu (2014), and Arcidiacono (2005) construct equilibrium models of higher education, but their analysis is not typically built from quasi-experimental variation.

The rest of this paper is organized as follows. The next section describes the institutional setting and data used in this project. Section 3 shows quasi-experimental estimates on students' price responsiveness. Then, section 4 presents a stylized model to interpret the role of financial aid on enrollment decisions and evidence of crowding out from past financial aid expansions. Then, section 5 presents the empirical strategy, the model of equilibrium, students' preferences, how the RD identifies price elasticity, and estimation details. Section 6 presents the parameter estimates, and section 7 provides the counterfactual results.

2 Institutional Setting and Data

This section describes the Chilean higher education system. Two institutional features are key to my empirical strategy: i) the most selective programs admit students using a centralized system and admission at other programs relies on GPA and test scores, and ii) scholarships are awarded using a discontinuous rule of assignment. This section also describes the data set used in this paper.

[3]See Deming and Dynarski (2009) for a survey.

2.1 Higher Education Programs

The Chilean higher education system has similar enrollment rates and a similar mix of public and privately owned institutions to the US.[4] Students can enroll in three types of institutions: Universities, Professional Institutes, and Technical Formation Centers. Universities focus on 4- to 5-year degrees, and the other two types of institutions focus on 2- to 3-year vocational degrees.

Total first-year enrollment in higher education stabilized in recent years (CNED, 2017). As a result, market dynamics in enrollment have a minor role in 2015, my current year of study. Between 2005 and 2011, first-year enrollment increased from 200 thousand students to 340 thousand (CNED, 2017). Bordon, Fu, Gazmuri and Houde (2016) study this expansion in detail, showing that between 2010 and 2015 six elite universities expanded their capacities on average by five seats per program, while the rest of the universities experienced a net reduction of one to four seats per program over a baseline of 46 seats per program.

2.2 College Admission Systems in Chile

Admissions are based on high-school GPA and a national admissions exam. High school graduates can register once per year to take the national admission test (Prueba Selección Universitaria, PSU), an SAT-type exam with four sub-tests: Mathematics, Language, and the choice of taking Science or History. After receiving their scores at the end of the year, students choose institution-major combinations and can apply for admissions in the two separate systems described below.

Table 1 summarizes the number, total enrollment, selectivity, and average tuition of programs in 2015 by type of institution and admission system. The centralized admission system hosts programs that are between one and three thousand dollars more expensive than the average program, and the least qualified admitted student in this system has one standard deviation higher score compared to her counterpart at the decentralized universities. Additionally, 25% of students enrolling in the decentralized system do not take the national admission test.

The centralized admissions system groups 33 out of all 58 universities in the country.[5] It accounts for 76% of first-year university enrollment among same-year high school graduates.[6]

[4] See Solis (2017) and Hastings, Neilson and Zimmerman (2016, 2017) for direct comparisons between both systems.

[5] Some form of coordination using an exam in the admission process has existed since 1967.

[6] 47% of first year enrollment at all institutions. Corresponds to 26% among all first year students in 2015, and 57% among all first-year university students in that year. The difference between these percentages corresponds to older students that enroll years after graduating from high school.

It is also the most selective part of the higher education system in Chile, with programs requiring an average score in Mathematics and Language above the 45th percentile just to be considered in the admission process.

The centralized admission system opens once every year after test results are announced, allowing students to rank up to ten college-major combinations. Programs rank applicants based on a weighted score that is a function of Mathematics, Language, GPA, and either history or science scores. Given students' rankings, program-specific scores, and capacities, the system offers students a seat at most at one program in such a way that no student-program pair prefer each other and are not assigned together. This is done using an algorithm built on Gale and Shapley (1962)'s student-proposing deferred acceptance algorithm described in detail in Appendix A.2.[7] This process creates a cutoff for admission at each program, which corresponds to the score of the least qualified admitted student. Rejected students are entered into the waitlist for that program. After students decide whether to take the admission offer, in a second instance of the centralized admission system, waitlisted students might be offered admission.

The use of the student proposing deferred-acceptance algorithm guarantees that in absence of cost and a limit to the number of programs students can rank, and that weighted scores do not include ties, students are assigned to their most preferred option among programs where they would be admitted (Gale and Shapley, 1962).[8]

Three aspects of the centralized system might affect this. First, the system allows students to rank up to ten options. If binding, students would need to strategically choose what to rank, leading to the possibility that students are not assigned to their most preferred option among those where they are eligible. However, among all students, just 1.5% rank ten options and only 0.02% are admitted in their tenth option. Second, some institutions impose a limit to the last position where a student can rank them to be considered for admission. Two of the 33 institutions will only admit students that rank them fourth or higher. However, the median institution imposes no limit, and the average requirement is to rank the institution 9th or less.[9] Additionally, 88% of students were admitted in one of their top three choices, so these restrictions are not binding to most students. Finally, the weighted score used by programs might include ties in the last admitted student, which the system solves by adjusting capacities to include all students with the same scores. However, this does not impose violations on stability (Ríos et al., 2014).

All other institutions admit students with no coordination and by directly receiving

[7] Institutions also have special admission systems for athletes and international students, but they represent a small part of the admission process.

[8] DA is also strategy-proof (Dubins and Freedman 1981, Roth 1982).

[9] Appendix A.5 shows the list of requirements by institution in the centralized system.

requests for enrollment. Programs at vocational institutions are not selective, while programs at the 25 universities outside the centralized system usually impose an ex-ante cutoff for admission based on admission test scores (PSU) and high school GPA. Appendix A.3 shows examples of these requirements for two of these institutions.

2.3 Financial Aid

In Chile, students can get financial aid from the government in the form of scholarships and a state guaranteed loan. Eligibility for these benefits is determined using cutoff rules for family income quintile and average Mathematics-Language admission scores. As a result, students are eligible only if they are below a certain income level and above a given score. Additionally, tuition subsidies are institution-major specific, with the average scholarship covering 80% of sticker tuition. Table 2 summarizes the scholarship programs for 4- to 5-year programs with their amounts and cutoffs for eligibility. Higher education institutions also provide some financial aid, but there is no data on their award size or its importance for the system. However, considering that the main objective they have is attract high-achieving students, and that these scholarships usually last only for the first year of a four- to five-year degree, they are likely to play a minor role compared to the government financial aid programs.

Students apply to all forms of financial aid by filling out a brief online form that self-reports their family income. This information is cross-checked with the Chilean tax office and is used to assign students into income quintiles.[10]

In this paper I focus on scholarships and how their targeting affects different groups of students. Figure 1 shows how scholarship eligibility expanded between 2011 and 2015. Over this period, students who were just below the eligibility cutoff for these scholarships were also eligible for the state guaranteed loan —that by 2015 could be used by students of all income levels whose average Mathematics and Language score was approximately above the 3th percentile. This means that students who by a small margin are not eligible for the scholarship could enroll in college using a state guaranteed loan, which Solis (2017) suggests eased credit constraints.

2.4 Data

The Ministry of Education of Chile provided access to several data sets on students: enrollment, admission test scores, family income quintiles, scholarship assignment, and other

[10]Students' per-capita family income is compared to income thresholds, constructed from a national socio-economic survey (CASEN), to determine income quintiles.

demographic characteristics. Each student has a unique identification number across all data sets. Enrollment information includes the exact program where the student enrolls, as well as characteristics of the program: type of institution, location, duration, posted tuition, accreditation, and area of knowledge. Student demographic characteristics come from a survey, administered to students during their registration for the admissions test, that includes parental education and type of high school students attended (public, voucher, or private), among other characteristics.

My main analysis sample focuses on the cohort of students that graduated from high school in 2014 and immediately took the admission test (PSU) to enroll in 2015. This restriction ensures that the sharp discontinuity in scholarship eligibility is not subject to manipulation through multiple test taking behavior and avoids having to model the dynamic aspect of older graduates who might start college years after finishing high school.[11]

This sample contains 171,011 students, whom I observe in 107,693 bins created from a subset of student demographic characteristics (type of high school, mother head of household, mother's education level, and region of residence), program of enrollment, income quintile, and financial aid status. For each bin, I also observe the average Math-Language score and average GPA. In this sample I closely replicate the regression discontinuity using the full data set, which makes me confident that the aggregation process is not a problem. The main restrictions of my current data are not having detailed information about individuals' test scores and observing income quintiles instead of deciles. However, observing GPA and average Math-Language score closely approximates the actual admission choice set that students face, and the fourth income quintile has a minor participation in scholarships through the seventh decile. Further details on this issue are presented in Appendix A.

Table 3 shows details for the population of students, their enrollment rates, and other observable characteristics used in estimation. In the data, I do not observe per capita income, but only the final income quintile used by the Ministry of Education to assign financial aid. There are 27% of students for whom I do not observe income quintile because they did not fill the application form for financial aid.[12]

I use a second dataset that contains program level information between 2008 and 2015. I use this sample to study the how past financial aid expansions affected enrollment of different groups of students.

[11] I consider only one year in this sample because of current data restrictions. A future version will use data from 2011 to 2015.

[12] Analysis of administrative data on parental income from another dataset shows that non-applicants to financial aid are similar to the wealthiest students who applied. This is consistent with the scenario where eligibility criteria for scholarships is public and known by many.

3 Enrollment Effects of Aid: Regression Discontinuity Estimates

Let t_i denote student i's average Mathematics-Language admission score, and I_i her family income that are used to determine scholarship eligibility. Let $\bar{t}$ be the test score eligibility cutoff, and $\overline{I}$ the income eligibility cutoff. Conditional of $I_i \leq \overline{I}$,

$$r_i = t_i - \bar{t} \tag{1}$$

determines scholarship eligibility ($r_i \geq 0$).[13] These eligibility rules are publicly known and publicized, but students have no control over their exact test score, creating a regression discontinuity design (RDD). This is the same strategy pioneered by Van der Klaauw (2002) and used in a growing literature by others (e.g. Goodman (2008), Cohodes and Goodman (2014)). In the Chilean context, Solis (2017) uses the same strategy to study the state guaranteed loan program.

Figure 2a plots scholarship assignment as a function of r_i among the income eligible population in the analysis sample, confirming the sharpness of scholarship assignment in this sample. Plotted points are conditional means for all applicants in a two-point bandwidth. The plots also show estimated conditional mean functions smoothed using a second order polynomial. Not everyone above the cutoff is awarded the scholarship, as only students enrolled at an eligible institution will receive it. The bottom panel shows the average enrollment rate at eligible institutions for different levels of the running variable. The jump in the average enrollment rate at the eligibility cutoff constitutes non-parametric evidence of the effect of scholarship eligibility.

I construct non-parametric RD estimates for the effect of scholarship eligibility on enrollment using the average Mathematics and Language score as the running variable among students with eligible income levels. This initial set of results provides the basis of the price variation used in the demand estimation. Specifically, I estimate a local linear regression of the form:

$$y_i = \gamma_0(1 - D_i)r_i + \gamma_1 D_i r_i + \rho D_i + \epsilon_i, \tag{2}$$

where the variable y_i is an indicator for enrollment of student i, x_i is the running variable centered at the discontinuity, D_i is an indicator for $x_i \geq 0$, and the coefficient of interest is ρ. Equation 2 is estimated from a kernel-weighted least squares fit, using a triangular kernel centered around the scholarship eligibility threshold and narrowing the data used in estima-

[13] Because I only observe income quintiles, I cannot exploit the discontinuity of eligibility on income.

tion to a data-driven bandwidth selected with the criteria used in Imbens and Kalyanaraman (2012). As it has been suggested by practitioners, I report results for multiple bandwidths and provide robustness of these results in Appendix B, including other bandwidth selection procedures and parametric specifications using higher order polynomials. None of these choices produced meaningful differences in the results.

Table 4 shows that being eligible for a scholarship increases enrollment by 9.5 percentage points from a basis of 28% enrollment at eligible institutions. Columns (2) and (3) show the extensive and intensive margin effect of scholarship eligibility, respectively. Being eligible for a scholarship increases enrollment at any institution by 6.5 percentage points over a basis below the cutoff of 69%. Column (3) shows that enrollment at ineligible programs drops by 3.1 percentage points over a below-the-cutoff basis of 34%. This is direct evidence that students trade-off prices and other program characteristics when deciding their enrollment, and that some students will enroll at eligible institutions only if being awarded a scholarship.

I show heterogeneity of these effects by estimating equation (2) for each of the three eligible income quintiles. Panel A in Table 5 shows that the effect of scholarship eligibility increases with income. Scholarship eligibility increases enrollment at eligible institutions by 7.7 percentage points (28.5% over the baseline rate) for students in the first income quintile, while it has an effect of 10.9 percentage points (37% over the baseline rate) for the third income quintile. This larger response from higher-income students mixes differential intensive and extensive margin responses. Panel B of Table 5 presents very similar responses on overall enrollment by income quintile, which are around 6.5 percentage points, and shows that as a proportion of the baseline, enrollments are very similar across quintiles (approximately 10%). The differences presented in panel A are partly due to the difference in substitution between vocational institutions and universities. Panel C shows that poorer students are less likely to substitute away from vocational/technical higher education institutions when offered a scholarship. This suggests that lower-income students are somewhat less responsive to price subsidies; however, a formal test of these differences does not reject the null of equal effects.

Finally, I consider a placebo test using the fifth and richest income quintile. Students in this quintile are not eligible for a scholarship, so their enrollment decisions should not be affected by crossing any threshold associated to scholarship eligibility. Using the common cutoff for the first three income quintiles, the last column of Table 5 shows little evidence of an effect and only a marginally significant result for one of the three measures of enrollment.

Appendix B reports results to address several possible threats to the validity of a causal interpretation of the results in Table 4 and 5. In particular, I look at the potential difference in demographic characteristics of students at both sides of the scholarship eligibility cutoff.

There are a couple of covariate contrasts that are significant, although very close to zero, and overall these gaps seem consistent with the idea that threshold crossing is indeed a good experiment.

Together, these results strongly suggest that enrollment decisions change discontinuously at the cutoff of scholarship eligibility. The positive effect of scholarships on enrollment is consistent with the evidence of a large quasi-experimental literature.[14] These results are best interpreted as the causal effect for individuals at the discontinuity. I will embed this quasi-experimental effect on a structural model and extrapolate to estimate preferences for the overall population imposing further restrictions that are discussed in section 5.

4 General Equilibrium Effects and Crowding Out

The evidence above shows that students respond to reduction in tuition by changing their enrollment decisions. I now develop a simple model to explain how expansions of financial aid eligibility can create crowding out. This framework will also suggest the primitives that I need to estimate in order to measure crowding out. Then, I present direct evidence of crowding out using past financial aid expansions in a difference-in-differences strategy.

4.1 A Stylized Model

This subsection presents a stylized model to provide the intuition for crowding out, the role of colleges' admission cutoffs, and the objects quantified in my empirical strategy. My analysis builds on Azevedo and Leshno (2016), who show the role of admission cutoffs as prices in a general two-sided market with a continuum of agents on one side of the market, and on Agarwal (2017), who presents an empirical discussion of price and quantity policies in these types of markets.

Consider a unit mass of students distributed along three dimensions: willingness to pay for the selective college (W), income (I), and a scalar test score used for admission at the selective college (t). In this model everyone enrolls, and students decide between two options: one selective college and another non-selective college. The selective college has a binding capacity constraint that is initially fixed, while the non-selective college can admit all applicants. Willingness to pay at the non-selective college is normalized to zero, so that students with $W \geq 0$ will prefer to attend the selective college. Applicants to the selective college are admitted based on their test scores, creating a cutoff admission rule. Financial aid to attend the selective college is initially targeted to students with income $I \leq 0$.[15]

[14] See Deming and Dynarski (2009) survey of this.

[15] Considering a subsidy only to the selective college mimics the Chilean scholarships studied before. It can

Figure 3a shows the group of applicants to the selective college in the space (I, W), and in this model corresponds to everyone with $W \geq 0$. A subsidy s to study at the selective college for students with $I \leq 0$ implies that all students whose willingness to pay is $W - s \geq 0$ apply to the selective option. Receiving a scholarship or making the current scholarship more generous compensates for a negative willingness to pay, attracting new applicants that have lower valuation for the selective college. Figure 3b shows in dark area the applicants that would be added in the case where a more generous scholarship is offered to everyone (free tuition).

The selective college admits the most qualified applicants until reaching its capacity limit. After a tuition subsidy increases the number of applicants, if new applicants are more qualified than the baseline admitted students, the last admitted student would have a higher score, raising the admission cutoff. In that case, some of the students admitted at the baseline will be displaced by newcomers.

Figure 4a shows the group of accepted students at the selective college in the space (I, t), with the normalization of the initial admission cutoff to be $t = 0$. A scholarship to a small fraction of students (of mass 0) will induce new applicants to enroll in the selective program if they have test scores above the initial admission cutoff. This is the effect captured by the regression discontinuity in subsection 3. However, in the presence of more generous and less targeted scholarships, the pool of applicants increases as Figure 3b shows. Figure 4a presents the case where new applicants have higher scores than the initial admission cutoff, in which case the admission cutoff needs to be raised because of capacity constraints, thereby displacing students in the red area. The importance of crowding out and who would be affected is determined by students' preferences, test scores, and scholarship targeting.

This model can be used to understand complementary policies to free tuition that could alleviate crowding out. In particular, I consider two policies that are often seen in practice: (i) Capacity expansion and (ii) Means-testing. In the model, the mass of students in the red area of Figure 4b represent the supply expansion needed to absorb all new applicants and keep the admission cutoff at the pre-free college level. This is a direct and simple way to deal with crowding out, but it might not be feasible if the required expansion is too large. If the objective was to keep enrollment rates by income level at least at baseline levels, without worrying about the identity of who is accepted at the selective college, then a smaller supply expansion would be necessary, but its magnitude will depend on the empirical distribution of preferences, test scores, and income.

A more sophisticated means-testing of financial aid might also alleviate the effect of

also be interpreted as a scholarship for a proportion of the tuition. As selective programs are more expensive this translates into a bigger subsidy to attend the selective option.

crowding out. To incorporate the objective of making the policy universal, I consider a linear schedule of financial aid that depends on income. Figure 5 shows different means-testing policies and the corresponding set of new applicants of each policy. These policies reduce the set of new applicants with high-income by giving poorer students a larger subsidy. Whether these policies reduce crowding out or not depends on the mass of students with high test scores that each policy attracts to the selective college. Section 5 explains how to estimate the components of this model to quantify crowding out and who is affected. Next, I show direct evidence that crowding out has happened in past eligibility expansions.

4.2 Effects of Previous Expansions

I estimate the effect that earlier scholarship eligibility expansions had on the enrollment of low-income students who were eligible for these benefits throughout the last decade. Figure 1 summarizes all the changes in eligibility for 4-year program scholarships. The first change happened after a period of constant eligibility criteria from 2007-2011, when only high-achieving students in the poorest 40% were eligible, and I look at expansions in the period from 2012-2015, when a new income quintile was included and students could access scholarships with half a standard deviation lower scores.

I use a difference-in-differences strategy that exploits the changes in eligibility criteria over time and the differential exposure that programs had to the expansion. In particular, I approximate the exposure that each program had to these expansions using the average share of students in the poorest 40% between 2008 and 2011. This intends to proxy programs' chances of receiving new scholarship beneficiaries after the introduction of financial aid expansions. I estimate the following equation,

$$y_{jt} = \alpha + \rho \text{share}_j \cdot 1\{t > 2011\} + \tau_t + \tau_j + \epsilon_{jt} \tag{3}$$

where y_{jt} is the outcome of interest for program j and year t, share_j is the average share of low-income students between 2008 and 2011 at program j, τ_j and τ_t are program and time fixed effects, and ρ is the parameter of interest that measures the effect that the post-2011 financial aid expansions had on programs with a higher pre-2012 share of low-income students.

Estimates of equation (3) show negative effects on enrollment for low-income students that were eligible for scholarships throughout 2007 and 2016. This can be seen in columns (1) to (3) of Table 6, where I present different specifications of equation (3) and the dependent variable is the share of students enrolled in program j coming from the poorest 40%. All

specifications are stable and suggest that programs with one standard deviation higher share of low-income students in the pre-expansion years experienced a reduction of approximately 5 percentage points (10% over baseline) in their share of low-income students. The results therefore reject the null of no effect of the size of the pool of eligible students on enrollment for low-income students who were eligible for scholarships before 2012.

On the other hand, columns (4) to (6) of Table 6 show estimates of equation (3) using admission cutoffs as dependent variable. I find that programs with one standard deviation higher share of low-income students in the pre-expansion years had an increase of 0.3 standard deviations of test score in their admission cutoff post-eligibility-expansion. These results are in line with the prediction of the stylized model and with the hypothesis that financial aid expansions increase competition for programs. Finally, columns (7) to (9) present the same exercise using enrollment as outcome. The coefficients suggest that total enrollment at programs with a one standard deviation higher share of low-income students in the pre-expansion period results in a 10% reduction in total enrollment. This reduction in capacities might partly explain the increase in cutoffs and could be part of a strategy that programs followed to increase selectivity after 2011. Together these effects suggest that crowding out could be the outcome of financial aid expansions. Appendix C shows that the parallel trends assumption needed to causally interpret the difference-in-differences estimates is mostly met for the share of low-income students, but that some pre-trend exists for cutoffs and enrollment, and that therefore their causal interpretation might be problematic.

These results are best interpreted as a test of the null hypothesis of no crowding out because the existence of displacement or spillovers complicates the causal interpretation of most quasi-experimental strategies. If a financial aid expansion pushes low-income students out of programs where competition increased, they might move to programs with lower demand. This means that the increased demand affects both treated and control programs, implying that non-randomized evaluation will overestimate the reduction in low-income students' enrollment. Specifically, this scenario implies a violation of the Stable Unit Treatment Value Assumption (SUTVA).[16] Nevertheless, in the absence of crowding out, the empirical strategy I used is a valid test for the existence of crowding out. This problem has been long recognized in the job placement assistance literature, where recent studies use clustered experimental variation to address this issue (Crepon, Duflo, Gurgand, Rathelot and Zamora, 2013). For this reason, and because I am interested in studying the design of universal financial aid policies, my main empirical strategy uses an equilibrium assumption and a local but large price variation to identify how free tuition would affect students' demand for college.

[16]Under SUTVA, potential outcomes for any student do not change with the treatment assigned to other individuals.

5 An Empirical Model of the College Market

To quantify the consequences of a tuition-free policy on enrollment, I build on Fack et al. (2017) to create student-specific choice sets using realized admission cutoffs and estimate a random utility model where the price coefficient is identified by the local price variation induced by the regression discontinuity design of scholarship eligibility. This section describes this empirical strategy by first presenting the equilibrium notion that justifies using admission cutoffs to create individual choice sets. In subsection 5.2, I develop a general random utility model and present the parametric version I estimate. In subsection 5.3, I present an identification result that justifies the use of the regression discontinuity design to identify price coefficients in a random utility model. Finally, I present some of the estimation details, with further details provided in Appendix E.

5.1 Equilibrium

I assume that matches between students and programs are pairwise stable, i.e. each student enrolls at her most preferred program for which she is eligible for admission. Formally, let $i \in \mathcal{I} = \{1, 2, \ldots, N\}$ be the set of students to be matched with a finite set of programs $\mathcal{J} = \{1, 2, \ldots, J\}$. Each program j has a capacity c_j, which is the number of students it is willing to admit. Each student i has a preference ordering $\succeq_i$ over the set $\mathcal{J} \cup \{0\}$, where $\{0\}$ denotes not enrolling in college, and a vector of scores $\mathbf{e}^i \in [0, 1]^J$ that describe programs' ordinal preferences for the student.[17] That is, if $e^i_j > e^{i'}_j$, then program j prefers student i to student i'. Because in Chile programs' preferences depend only on these weighted scores, I assume that all students are acceptable to programs.

A match, given by the function $\mu : \mathcal{I} \to \mathcal{J}$, describes the allocation of students to programs. Let $\mu^{-1}(j)$ denote the set of students enrolled in program j.

A pairwise stable match satisfies two properties for all student $i \in \mathcal{I}$:

1. Individual Rationality: $\mu(i) \succeq 0$.

2. No Blocking: if $j \succ_i \mu(i)$ then for all $i' \in \mu^{-1}(j)$, $e^{i'}_j \geq e^i_j$.

Individual rationality implies that there is no student enrolled in college who would rather not. This is a minimum requirement to interpret enrollment decisions as revealed preferences, and it accords with the voluntary nature of enrollment. The assumption that all students are acceptable to programs makes the allocation individually rational to programs as well.

[17] In the Chilean context this corresponds to the weighted score using GPA and the national admission test scores.

The no blocking condition means that no student prefers a program (to her current match) that would admit her in place of the least qualified admitted student in the program if it is using all its capacity. This least qualified admitted student in each program j defines the admission cutoff at that program,

$$P_j = \min_{i \in \mu^{-1}(j)} e_j^i \quad \forall j \in \mathcal{J}, \tag{4}$$

with $P_j = 0$ for programs that do not use all their capacity. Based on these cutoffs, student i is eligible for admission at program j if $P_j \leq e_j^i$ and this defines her choice set,

$$S(\mathbf{e}_i, \mathbf{P}) = \{j \in \mathcal{J} | P_j \leq e_j^i\} \tag{5}$$

Proposition 1 from Azevedo and Leshno (2016) for the continuum case highlights the relation between cutoffs and pairwise stability.

Proposition 1. μ is stable if and only if $\mu(i)$ is student i's favorite program among those in $S(\mathbf{e}_i, \mathbf{P})$ for all $i \in \mathcal{I}$.

Therefore, a pairwise stable matching corresponds to each student choosing her favorite program conditional on being accepted at the vector of cutoffs $\mathbf{P}$.

The use of pairwise stability as an equilibrium assumption is appropriate for college admissions systems with low frictions. It is motivated in my case by the general admissions rules used in college admissions. Unlike American universities, Chilean colleges use formulaic aggregates of high-school test scores to determine admission. A threshold score for each college is published annually, and these scores are stable one year after the next. Students should therefore be aware of which programs are likely to admit them after their tests have been scored. Moreover, most selective universities use a centralized stable matching algorithm to further avoid instances where a student is not enrolled in her most preferred eligible option.

A potential threat to this assumption is lack of knowledge about admission requirements at programs outside the centralized admission system. Appendix A.3 presents examples of information on the minimum test scores and grades required for admission at two universities inside and outside the centralized system. Similar information is given to students at fairs that high schools hold, and it can be easily accessed online.[18] A second caveat is that strategic ranking behavior leads to ex-post regret on the assigned program. As explained

[18] Hastings, Neilson and Zimmerman (2016), using a survey, report that 40% of students get information at these fairs.

in subsection 2.2, students are limited to ranking up to ten programs, and a minority of institutions imposes a lower cap on the maximum number they will consider. However, these restrictions do not seem to be binding as only 1.5% of students rank ten options, and 88% of students are accepted at one of their top three options. The stability assumption may be implausible in other college markets where admission criteria are not as transparent and publicly available, and where selective institutions do not hold a centralized assignment system that ensures violations do not occur.

I use realized cutoffs for programs in the centralized system and the average Mathematics-Language score of the least qualified enrolled student for the rest of the 4-year programs to construct student-specific choice sets. While the realized cutoffs are unpredictable for students (with cutoffs at the centralized system with a standard deviation of 0.18 standard deviations of the test), they are very stable from one year to the next, with a correlation of 0.95.[19] Cutoffs from previous years are publicized by universities before students apply in the case of the centralized system, and they are usually established upfront for programs in the decentralized system. This creates a scenario where, up to the change in the realized cutoffs, students know their eligibility for admission before applying. Absent changes in the cutoffs from year to year, students would need to apply only to one option. Being able to rank multiple options helps students deal with cutoff uncertainty and ensures they are admitted at their preferred option once cutoffs are realized in the current year. The persistence of cutoffs at some programs makes students select their ranked alternatives, omitting options for which their scores are too far down from the previous year's cutoff.[20]

Subsection 5.4 explains how I use this assumption to construct student-specific choice sets in my data.

5.2 Preferences

I follow the discrete choice literature modeling the latent indirect utility that represents the preference ordering ($\succeq_i$) as a function of student observed characteristics, and programs' observed and unobserved characteristics. The indirect utility student i gets from enrolling in program j is given by

$$\begin{aligned} u_{ij}(x_j, z_i, w_i, \gamma_i, \epsilon_{ij}, \delta_j; \theta) &= v(x_j, z_i, \gamma_i, \epsilon_{ij}; \theta) - \pi(w_i)\text{price}_{ij} + \delta_j \\ \delta_j &= \beta x_j^1 + \xi_j, \end{aligned} \tag{6}$$

[19] Regressing cutoffs using only last years' cutoffs results on an R^2 of 0.9986.

[20] Appendix A.4 presents graphical evidence of this behavior. Artemov, Che and He (2017) present evidence of this type of behavior in the Australian college admissions.

where x_j is a vector of observed characteristics for program j and x_j^1 is one of those characteristics, z_i is a vector of observed student i's characteristics, and w_i are student characteristics other than her admission test scores. ξ_j is a program-specific unobserved characteristic, γ_i captures idiosyncratic tastes for program characteristics, ϵ_{ij} contains idiosyncratic taste for program j, $\pi(w_i)$ is a student-specific price responsiveness, and price_{ij} is the tuition student i faces for program j, which is constructed as program j's tuition minus the scholarship student i gets enrolling at program j. Scholarships are determined by student i's average Mathematics-Language score t_i and income eligibility. Conditional on a value of $t_i = t$ and on income eligibility, scholarships do not depend on the identity of students.

I follow Berry et al. (1995, 2004) and include ξ_j as an unobserved (to the econometrician) program component that captures a quality characteristic observed by students. The fact that programs might set prices considering the desirability captured in this unobserved component implies that $\text{price}_{ij} \not\perp \xi_j$.

This formulation allows for heterogeneous preferences, price endogeneity, and semi-additive preferences conditional on observables. Although quite general, equation (6) embeds four assumptions that I make throughout the paper. First, ξ_j is a scalar unobserved program characteristic that does not depend on the test score of student i, t_i. This assumption is made in much of the existing empirical work, and it restricts the form of the endogeneity problem. Second, price_{ij}, ξ_j, and a program characteristic, x_j^1, enter the indirect utility linearly. This assumption is commonly used in practice as well, and it implies that the program unobserved component and x_j^1 affect the utility only through δ_j, and linearity in price facilitates the extrapolation of preferences using the limited quasi-experimental price variation in my data. Third, students' indirect utility depends only on their own assignment and not on other students'. I make this assumption in order to focus on the causal effect of tuition, which is the main channel of interest in my counterfactual analyses. In this sense, this assumption does not limit my ability to include baseline peer composition characteristics, but it limits my analysis of the effect that changes in peer composition have on demand (coming from price changes). These first three assumptions are standard in the school choice literature (e.g. Hastings et al. (2006), Neilson (2013), Fack, Grenet and He (2017), Abdulkadiroglu, Agarwal and Pathak (2017)). Finally, the source of variation that allows me to identify price coefficients is based on the discontinuity of prices with respect to t_i, and therefore I cannot identify heterogeneous price responses by test scores. This implies that $\pi(w_i)$ does not include t_i. However, students' price responsiveness is in principle allowed to depend flexibly on other observable characteristics.[21]

[21] I am working to get access to more years of data, which would allow me to incorporate test scores in the price sensitivity by using the change in eligibility cutoffs over years.

While my identification result does not make additional parametric assumptions, I use several assumptions to assist estimation in my sample. For estimation, I specify student i's indirect utility for program j as

$$
\begin{aligned}
u_{ij} &= \sum_{k=1}^{K} \alpha_k z_{ik} x_{jk} + \gamma x_j^{\text{sel}} \nu_i - \left(\pi_1 + \frac{\pi_2}{\max\{\underline{I}, I_i^s\}} \right) \text{price}_{ij} + \delta_j + \epsilon_{ij} \qquad (7) \\
\delta_j &= \sum_{k=1}^{K} \beta_k x_{jk} + \xi_j \\
u_{i0} &= 0
\end{aligned}
$$

where $\theta = \{\boldsymbol{\alpha}, \gamma, \boldsymbol{\pi}, \boldsymbol{\xi}, \boldsymbol{\beta}\}$ are the coefficients to be estimated, and $\epsilon_{ij} \sim$ iid type I extreme value distribution. I_i^s corresponds to the simulated per capita income of student i drawn from the empirical distribution of income in the national survey (CASEN)[22] conditional on student i's income quintile. The functional form of income allows for non-linear responses, ensuring that low-income students' utilities do not grow unbounded as income approaches zero. In practice, I use $\underline{I}$ to be 2 thousand dollars, which corresponds approximately to the 25th percentile of the income distribution.[23] The normalization of $u_{i0} = 0$ is without loss of generality. In estimated specifications, z_{ik} contains an indicator of public high school, an indicator of voucher high school, average between Mathematics and Language admission test scores, an indicator of being in the 40% poorest part of the population (defined using family income quintiles), an indicator of having a mother with no high school education, and an indicator of having a mother with high school education. Additionally, I include an indicator for program j being in the same geographic region as student i.[24] x_j considers: the share of students enrolled in program j that belong to the poorest 40% of the population, the share of students enrolled in program j that graduated from a public high school, an indicator of j being a STEM program, the average Math-Language admission score among enrolled students, and the number of students enrolled in the program. x_j^{sel} corresponds to the average Math-Language score of admitted students as a measure of program selectivity, which is allowed to have a random coefficient that allows for unobserved heterogeneity of preferences according to $\nu_i \sim N(0, 1)$, so that γ captures the standard deviation of this random component.

[22] This is the survey used to construct income quintile thresholds used administratively.
[23] I am working to provide robustness to this parametrization.
[24] Chile is administratively and geographically divided in fifteen regions.

5.3 Identification

This subsection illustrates the key insight that allows me to learn about the demand for college based on enrollment decisions and the regression discontinuity design of scholarship eligibility. As is customary in the identification literature, I do this by abstracting from sampling noise. I first present a simplified parametric model that highlights the role of the regression discontinuity design, followed by a formal discussion about identification that builds on Berry and Haile (2014).

Insights from Parametric Model

I start with a simplified parametric version of students' preferences, abstracting away income eligibility requirements for the scholarship, and from student-specific choice sets. Further simplifying the indirect utility in equation (7) we have,

$$u_{ij} = x_j\beta - \pi \text{price}_{ij} + \xi_j + \epsilon_{ij} \tag{8}$$

Because scholarship eligibility is determined by the average Mathematics-Language score, t_i, students with a common $t_i = t$ face all the same price for program j, which I denote as price_{jt}. Therefore, different values of t define different "markets". Given the parametric assumptions, market shares for the group of students with $t_i = t$ are given by

$$s_{jt} = \frac{\exp\left(x_j\beta - \pi \text{price}_{jt} + \xi_j\right)}{1 + \sum_k \exp\left(x_k\beta - \pi \text{price}_{kt} + \xi_k\right)}, \tag{9}$$

and the relation in (9) can be inverted to express

$$\ln s_{jt} - \ln s_{0t} = x_j\beta - \pi \text{price}_{jt} + \xi_j \tag{10}$$

The assumption that ξ_j does not depend on students' scores embedded in equation (6) implies that given the scholarship cutoff ($\bar{t}$), the variable $q_t = 1(t \geq \bar{t})$ is a valid instrument to estimate π. Intuitively, comparing the market share for program j for the group of students eligible for the scholarship with that of those who are not eligible provides information on the importance of prices for students' choices.

What follows next addresses the complications of the more general case of preferences in equation (6). First, students face different choice sets that are determined by GPA and test scores, which is a key component of the empirical strategy. Second, I provide conditions

under which the demand for programs is non-parametrically identified.

Identification of Demand

Conditional on a value of $t_i = t$ there is a multivariate conditional distribution for the vector of admission scores denoted by $\mathrm{F}(\mathbf{b}|t)$. A realization of $\mathbf{b}$ determines the choice set $S(\mathbf{b}, \mathbf{P})$, where $\mathbf{P}$ is the vector of admission cutoffs at all programs. The relevant programs in market t ($\mathcal{J}_t$) are those with a positive market share. I assume that in each market t there is a positive measure of students whose choice set is $\mathcal{J}_t$. This is reasonable in a market where students with higher scores are eligible for admission at more programs. I also assume that among this group of students, there is a positive measure choosing each program $j \in \mathcal{J}_t$. This assumes enough preference heterogeneity. I condition on all the other students' observable characteristics ($(z_i, w_i) = (z,w)$), omitting these variables from the notation. Then, a market t is defined by the group of programs $\mathcal{J}_t \cup \{0\}$, and by $\chi_t = (\boldsymbol{x}_t, \boldsymbol{p}_t, \boldsymbol{\xi})$, where $\boldsymbol{\xi}$ is a constant vector for all t as I have assumed in equation (6). Because of the assumptions made in equation (6), preferences depend on χ_t only through $\boldsymbol{\delta}_t$, which I modify here to be $\delta_{jt} = \beta x_j^1 + \pi \mathrm{price}_{jt} + \xi_j$.

Given this, we can define the market share for program j in market t as

$$s_{jt}(\boldsymbol{\delta}_t) = \sigma_j(\boldsymbol{\delta}_t) = \int \Pr\left(\arg\max_{k \in S(\mathbf{b},\mathbf{P})} u_{ik} = j | \boldsymbol{\delta}_t\right) d\mathrm{F}(\mathbf{b}|t), \quad j \in \mathcal{J}_t \cup \{0\}. \tag{11}$$

where $\sigma_0(\boldsymbol{\delta}_t) = 1 - \sum_{j=1}^{\mathcal{J}_t} \sigma_j(\boldsymbol{\delta}_t)$. Let $s_t = (s_{1t}, \ldots, s_{\mathcal{J}_t t})$ and $\sigma(\boldsymbol{\delta}_t) = (\sigma_1(\boldsymbol{\delta}_t), \ldots, \sigma_{\mathcal{J}_t}(\boldsymbol{\delta}_t))$.

Goods $\mathcal{J}_t$ are connected substitutes in δ_t if: i) $\sigma_k(\delta_t)$ is nonincreasing in δ_{jt}, for all $j > 0$, $k \neq j \in \mathcal{J}_t$, and ii) at each $\delta_t \in \mathrm{supp}(\delta_t)$, for any $\mathcal{K} \subseteq \mathcal{J}_t$ there is a $k \in \mathcal{K}$ and $l \notin \mathcal{K}, l \in \mathcal{J}_t$ such that $\sigma_l(\delta_t)$ is strictly decreasing in δ_{kt}. The next lemma establishes this property in my setting and its implication for identification of δ.

Lemma 1: (a) Goods $\{0\} \cup \mathcal{J}_t$ are connected substitutes in δ_t. (b) Given any market share vector $s_t = (s_{1t}, \ldots, s_{J_t,t})$ such that $s_{jt} > 0$ for all j and $\sum_{j=1}^{J_t} s_{jt} < 1$, and given the preference representation in equation (6), there is at most one vector $\boldsymbol{\delta}_t$ such that $\sigma_j(\boldsymbol{\delta}_t) = s_{jt}$ $\forall j \in \mathcal{J}_t$.

Proof: (a) Property i) of connected substitutes is implied by u_{ij} in equation (6) not depending on δ_{kt}, so that s_{jt} in equation (11) will not decrease with δ_{kt}. Property ii) is implied by u_{il} being strictly increasing in δ_{lt} and by the assumption over ($\mathrm{F}(\cdot)$) that each market has a positive mass of students choosing product k over all other options in the market, in particular having a program l in their choice set so that s_{kt} decreases with δ_{lt}.

Given part (a), part (b) is proved in Berry, Ghandi and Haile (2013), so the proof is omitted.

□

The property of connected substitutes provides a path of substitution among all programs in a market. Notice that each market might have different programs ($\mathcal{J}_t$), as not all students will be eligible for admission at all programs.

Given Lemma 1, for any s_t in the support we can write

$$\delta_{jt} = \beta x_j^1 - \pi(w)\text{price}_{jt} + \xi_j = \sigma_j^{-1}(s_t) \quad j = 1, \ldots, J_t \tag{12}$$

I impose here the location and scale normalizations

$$\beta = 1 \quad \text{and} \quad E[\xi_j] = 0 \quad j = 1, \ldots, J$$

Equation (12) is very similar to Berry and Haile (2014)'s, except that I further restrict preferences so that prices enter linearly in preferences. This will be important given the discreteness of the exogenous variation used to instrument prices, and the linear extrapolation conditional on $w_i = w$.

Identification of $(\pi(w), \sigma_j^{-1}(\cdot), \boldsymbol{\xi})$ can be established adapting the non-parametric identification result in Newey and Powell (2003) used in Berry and Haile (2014). Let $q_t = 1\{t \geq \bar{t}\}$, where $\bar{t}$ is the scholarship eligibility cutoff, and assume that:

Assumption 1: (a) For all $j = 1, \ldots, J_t$, $E[\xi_j | x_t, q_t] = 0$ almost surely. (b) For all functions $B(s_t)$ with finite expectation, if $E[B(s_t)|x_t, q_t] = 0$ almost surely, then $B(s_t) = 0$ almost surely. (c) price_t changes discontinuously at $\bar{t}$, and $\text{supp}(w_t|q_t = 0) = \text{supp}(w_t|q_t = 1)$.

Assumption 1.(a) is an exclusion restriction that treats non-price program characteristics as exogenous, and it justifies their use as instruments for the market shares in equation (12). Assumption 1.(b) is the analog of a rank condition in a linear model, and it requires instruments (x_t, q_t) to generate enough variation in s_t to distinguish different functions. This assumption clarifies the importance of the linearity assumption for prices. Because q_t takes only two discrete values, not having price_t inside the non-linear function $\sigma_j(\cdot)$ weakens the requirement on the role of x_t as instrument for prices. Finally, assumption 1.(c) states the discontinuity of prices on t, and a common support on the price heterogeneity covariates (w_t). This last assumption can be interpreted as a no-sorting condition that is natural in

the regression discontinuity design context, where students in both sides of the cutoff have similar observable characteristics that determine heterogeneous price response.

Theorem 1: Under the representation of preferences in (6), suppose Assumption 1 holds. Then, $(\xi_1, \ldots, \xi_J)$ is identified with probability 1, $\pi(w)$ is identified in the support of w and $\sigma_j(\delta_{jt})$ is identified on the support of δ_{jt}.

Proof: Under lemma 1, we can write

$$E[x_j^1|q_t, x_t] - \pi(w)\text{price}_{jt} + E[\xi_j|q_t, x_t] = E[\sigma^{-1}(s_t)|q_t, x_t] \tag{13}$$

and by assumption 1.(a),

$$E[\sigma_j^{-1}(s_t)|q_t, x_t] - x_j^1 - \pi(w)\text{price}_{jt} = 0 \quad \text{a.s.}$$

Suppose there is another function $\tilde{\sigma}^{-1}$ satisfying

$$E[\tilde{\sigma}_j^{-1}(s_t)|q_t, x_t] - x_j^1 - \pi(w)\text{price}_{jt} = 0 \quad \text{a.s.}$$

Letting $B(s_t) = \sigma^{-1}(s_t) - \tilde{\sigma}^{-1}(s_t)$, this implies

$$E[B(s_t)|x_t, w_t] = 0 \quad \text{a.s.}$$

and by assumption 1.(b), this requires $\tilde{\sigma}^{-1} = \sigma^{-1}$ almost surely, implying σ^{-1} is identified.

Given that both x_j^1 and price_{jt} are observed, and σ^{-1} is identified, evaluating equation (13) above and below the scholarship cutoff $\bar{t}$, and for all different values of $w \in \text{supp}(w)$, identifies the function $\pi(w)$ in the support of w. Then, ξ_j can be identified for each $j \in \mathcal{J}$. □

Intuitively, as in the parametric case, having students face different prices because of the scholarship eligibility rules provides variation to identify price coefficients. If market shares (or their inverse) do not change when going from market t to a market just above the eligibility cutoff ($\bar{t}$), then that indicates a small absolute value of $\pi(w)$. I use this intuition in the estimation section to construct moment conditions that contribute identifying $\pi(w)$. The proof clarifies that w_i cannot contain the running variable t_i, as for a given value of t there is no variation of the instrument, and therefore price responses that vary by t_i are not identified.

5.4 Construction of Student-Specific Choice Sets

In this part I first describe how I deal with the large number of alternatives students face. Then, I show how I construct student-specific choice sets $S(\mathbf{e}_i, \mathbf{P})$.

Reducing the Large Choice Set Dimensionality

In my setting, including all programs would lead to eight thousand alternatives in a single national market. In principle, this would mean having each of the 171 thousand students choose among thousands of programs. This is computationally intractable due to the slow computing of such a large vector $\boldsymbol{\delta}(\boldsymbol{\theta})$, and the number of alternatives is far larger than any application in the literature. For this reason I modify students' choice sets and the structure of the unobserved program component with the objective of preserving the identity of selective programs (approximately two thousand) without creating aggregates.

I use a procedure that leads to the estimation of the following model, which combines equation (7) and the grouping of the unobservable component of programs,

$$\begin{aligned} u_{ij} &= \sum_{k=1}^{K} \alpha_k z_{ik} x_{jk} + \gamma x_j^{\text{sel}} \nu_s - \sum_{l=1}^{L} \pi_l w_{il} \text{price}_{ij} + \delta_{g(j)} + \epsilon_{ij} \\ \delta_{g(j)} &= \sum_{k=1}^{K} \beta_k x_{jk} + \xi_{g(j)} \end{aligned} \tag{14}$$

with $g(j)$ being the group to which program j belongs, and $g(j) \in \mathcal{G} = \{1, \ldots, G\}$ is the set of all different groups.

The first step in reducing the dimension of the problem to group all vocational programs reducing the number of alternatives. This creates three aggregates (one per type of institution) of non-selective meta-programs included in all students' choice sets. I build similar aggregates for outside of each students' area of residence (north, south, and capital). I use enrollment-weighted averages of the characteristics of all these alternatives in estimation.

To deal with the remaining large number of alternatives (2,368 in total), I take advantage of two features of the Chilean context: (i) The choice of program is highly concentrated geographically, with less than 5% students choosing a program outside their zone of residence: north, capital, and south of Chile.[25] This motivates my decision of splitting the national market into three separate large geographical markets. Each market includes the alternative of enrolling outside the region in a two- or a four-year institution. Additionally, (ii) δ_j is

[25] Additionally, I do not find evidence that the scholarship has any effect on studying outside of the zone of residence.

meant to measure program-specific observable and unobservable characteristics, except for price. In Chile, programs hosted by the same institution and area of knowledge usually share the same faculty and building, and they might share some common curriculum during the first semesters. Leveraging this fact, I pool small programs together and have them share a common meta-program fixed effect ($\delta_{g(j)}$).

The features mentioned before motivate the following algorithm to pool unobserved components of programs together: (i) In a first step I identify all programs that have a market share in their area (north, south, and capital) of at least 0.5% (more than 300 students) and I let them have a single unobserved component. There are only two programs this large. The rest of the programs are aggregated as follows: (ii) I group together programs that share the same area of knowledge, institution, and geographic region, so that they are likely to share the same resources. This results in 41 meta-programs with a market share above 0.5% and formed based on 482 programs. (iii) I further group the remaining programs by using area of knowledge and institution, which creates another 49 meta-programs based on 1,557 original programs. (iv) Finally, among the few remaining programs (327), I form 6 meta-groups using area of knowledge and participation in the centralized assignment system. This process leads to 113 meta-groups used to facilitate computation. Further details of this process are presented in Appendix D. Results of the structural estimation are robust to decreasing the minimum share to be 0.1%, which results in 421 meta-programs.

Construction of Choice Sets

I construct admission cutoffs ($\mathbf{P}$) by reading the realized cutoffs in the centralized admission system (1,419 programs) in 2015, and for the rest of the college programs I assumed that admission was based on the average of Mathematics and Language test scores so that the cutoff for admission is the minimum average score among enrolled students. Appendix A.3 shows examples of two colleges outside the centralized system that use this as one of their main criteria. As mentioned above, vocational programs are non-selective, so I include the vocational option in all students' choice sets.

Finally, because of current data restrictions, I only observe the average Mathematics and Language score and GPA. For programs in the centralized admission process, I approximate the weighted score used at each program in the centralized system using the GPA-specific weight and assigning the rest of the weight to the average Math and Language score.[26] I assess this approximation by using another data set that contains all scores, providing an exact construction of choice sets. I find that my procedure includes or excludes wrongly 13%

[26]In reality this portion of the weight is shared between Mathematics, Language and a specific test of History or Science.

of programs in the centralized admission system.[27]

In sum, each student's choice set contains three aggregates for vocational programs in different types of institutions in her region, all the selective programs in her region for which she qualifies for admission, and two options for studying outside her region of residence: a vocational and a 4-year program.

5.5 Estimating Preference Parameters

I estimate the parameters θ in equation (7) starting from the moment condition:

$$E[y_{ij} - E(y_{ij}|x, z, w; \theta_0)|x, z, w] = 0$$

where $y_{ij} = 1\{j \in S(\mathbf{e}_i, \mathbf{P})$ and j is chosen$\}$, θ_0 is the true parameter vector, and (x, z, w) are observable characteristics. I form unconditional moments in the usual way, $g_i^s(\theta) = (y_{ij} - \hat{E}(y_{ij}|x, z, w; \theta))h(x, z, w)$ and choose θ to minimize the function

$$\hat{Q}_n(\theta) = \left[N^{-1} \sum_{i=1}^{N} g_i(\mathbf{x}, \mathbf{z}_i, \mathbf{w}_i, \theta) \right]' W \left[N^{-1} \sum_{i=1}^{N} g_i(\mathbf{x}, \mathbf{z}_i, \mathbf{w}_i, \theta) \right],$$

where W is a matrix of weights described below. I provide additional details on the estimator and the optimization algorithm in Appendix E.

I estimate the parameters combining three sets of moments that define $g_i(\mathbf{x}, \mathbf{z}_i, \mathbf{w}_i, \theta)$:

1. **Program-student characteristic interactions:** The covariance of the characteristic of the program where a student enrolls and her attributes (e.g., the covariance of type of high school the student attended and the share of students from public high school enrolled in that program):

$$\frac{1}{J} \sum_{j=1}^{J} (y_{ij} - \hat{E}(y_{ij}|x, z, w; \theta)) x_j^k z_i^k \quad \forall k = 1, \ldots, K$$

2. **Market Shares:** The market shares of each meta-program in each geographic area. Let a_i be the area student i lives in and a_h the area of program h with $a_i, a_h \in$ {North,South,Capital}, and N_{a_h} the number of students in area a_h:

[27] A future version of this paper will use all information necessary to construct the full choice set.

$$\frac{N}{N_{a_h}} 1\{a_i = a_h\} \sum_{j=1}^{J} 1\{g(j) = h\}(y_{ij} - \hat{E}(y_{ij}|x, z, w; \theta)) \quad \forall h = 1, \ldots, G$$

3. **Regression Discontinuity:** Following the intuition in the identification section, I construct the difference in the market share of programs where the scholarship can be used among students at both sides of the eligibility cutoff. Let $\mathcal{J}^E \subseteq \mathcal{J}$ be the set of programs eligible for the scholarship, $\phi_{ij} = 1\{|t_i - \bar{t}| \leq h\}\kappa_h(t_i - \bar{t})$, and $\kappa_h(x)$ be the normal kernel with bandwidth h chosen to be the same as the optimal bandwidth using Imbens and Kalyanaraman (2012). The moments used are three:

   - The local difference in the market share of eligible programs above and below the scholarship eligibility cutoff:

   $$\sum_{j \in \mathcal{J}^E} \phi_{ij} \cdot (y_{ij} - \hat{E}(y_{ij}|x, z, w; \theta))$$

   - The relation between the difference in market shares and student characteristics w:

   $$\sum_{j \in \mathcal{J}^E} \phi_{ij} \cdot (y_{ij} - \hat{E}(y_{ij}|x, z, w; \theta)) w_{il} \quad \forall l = 1, \ldots, L$$

   - The difference in market share for programs of different levels of selectivity:

   $$\sum_{j \in \mathcal{J}^E} \phi_{ij} \cdot (y_{ij} - \hat{E}(y_{ij}|x, z, w; \theta)) x_j^{\text{sel}}$$

Together these moments identify $\theta = \{\boldsymbol{\alpha}, \gamma, \boldsymbol{\pi}, \boldsymbol{\delta}\}$, and the contribution of each set of moments follows from my identification result and from Berry, Levinsohn and Pakes (2004). The first two sets of moments follow Berry et al. (2004) and help in estimating $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$, respectively. The third set of moments are motivated by the role of the regression discontinuity design in the identification of $\pi(w)$, and its first two components are crucial to identify the price coefficients $\pi(w)$. I use income quintile-specific moments to capture potential price response heterogeneity. Finally, interacting the market share difference with x_j^{sel}, which captures selectivity, helps in identifying γ, which measures the importance of deviations from the IIA property in the substitution patterns between price and selectivity.

As mentioned above, I use Income_i to add price response heterogeneity. I only observe

family income quintiles, which are determined based on per-capita family income, and thresholds of income determined in a household survey called CASEN. I use the observed quintile to draw per capita annual income from the empirical conditional distribution in this survey.

Given one draw of income from the survey and one draw of $\nu_s \sim N(0,1)$ I can express choice probability of student i for a program $j \in S(\mathbf{e}_i, \mathbf{P})$ as:

$$P_{ij}^s = \frac{\exp\left(\sum_{k=1}^K \alpha_k z_{ik} x_{jk} + \gamma x_j^{\text{sel}} \nu_i^s - \sum_{l=1}^L \pi_l w_{il}^s \text{price}_{ijt} + \delta_{g(j)}\right)}{1 + \sum_{j'=1}^J \exp\left(\sum_{k=1}^K \alpha_k z_{ik} x_{j'k} + \gamma x_{j'}^{\text{sel}} \nu_i^s - \sum_{l=1}^L \pi_l w_{il}^s \text{price}_{ij't} + \delta_{g(j')}\right)},$$

Because the precision of the estimator depends on $N \cdot S$ where S is the number of simulations, and I have a large N, I use one draw of Income and ν for each student.

5.6 Econometric and Computational Issues

I implement the estimation by using the nested fixed point algorithm developed by Berry (1994), applied in Berry, Levinsohn and Pakes (1995, 2004), and in a large body of literature. The details of this algorithm are fairly standard so I leave them to Appendix E for interested readers.

Standard Errors

I compute the asymptotic variance for the Method of Simulated Moments. Let Δ be the derivative of the moments, $\Delta = \nabla_\theta g(\theta)$, then the asymptotic variance-covariance matrix is given by

$$V = (\Delta' W \Delta)^{-1} \Delta' W \Omega \Delta (\Delta' W \Delta)^{-1}, \tag{15}$$

where $\Omega = \Omega_a + \Omega_s$, with Ω_a corresponding to the variance-covariance of the moments if they were not simulated, and Ω_s is the additional variance introduced by the fact that the moments are simulated. Further details on computation of these two components of Ω are included in Appendix E.

Finally, W is chosen to be $\hat{\Omega}^{-1}$ in a two-step procedure in the overidentified estimates.

6 Estimates

This section presents estimates from two models. The first one has rich substitution patterns based on student and program observable characteristics, but restricts equation (7) by setting

the price coefficient to be common across students and not allowing a random coefficient on program selectivity. The second model uses the full specification in equation (7). I use the comparison between both models to assess the importance of a heterogeneous price response. Both models are estimated using a similar set of moments described above. The common price model is just identified, while the income-heterogeneous price coefficient model includes RD-style moments for each income quintile and an interacted version with program selectivity to help identify the random coefficient.

Next, I present results of students' preferences for program characteristics translated into dollar equivalents and willingness to pay for different types of program characteristics. Then, I present a model fit exercise for these estimates. Appendix F discusses the underlying parameters and robustness to the decisions made in subsection 5.4.

6.1 Preferences

Table 7 shows the average price elasticity across programs and students by income quintile for both specifications. This is a key input for the counterfactuals, as the response to free tuition will be mediated by students' willingness to substitute away from their current choice when tuitions are subsidized. Both models predict that most students are inelastic. In principle, this could be exploited by a profit-maximizing institution. However, all colleges in Chile are non-profit by law. At the same time, selective institutions clear the excess of demand at current tuition levels relying on test scores, which is evidence of their multiple objectives. Table 7 also shows that higher-income students are more elastic. This is consistent with the regression discontinuity results by income quintile in section 3. On the other hand, differences in the regression discontinuity across income quintiles are not statistically significant, which might make the first model more appropriate. I will proceed to comment on the results for both models.

Panel A of Table 8 presents the estimated preferences for programs in thousand dollar equivalent terms, evaluating the second model at the average income for the poorest 20% and wealthiest 20% students. The estimated value of a one standard deviation higher proportion of students from a public high school at an otherwise identical program is about -$6,000 in the first model, while ranging between that value for the richest 20% and -$14 thousand dollars for the poorest 20% in the second specification. Although some coefficients differ in sign between both specifications, in general, the first model shows coefficients that are between the valuations of the poorest and richest in the second specification. Similarly, students are willing to pay $6,000 for programs with one standard deviation lower share of enrolled students in the poorest 40%. Estimates from both models suggest substantial

heterogeneity for program characteristics across different types of students.

While the academic quality, selectivity, and ultimately the value added of programs are likely the most important determinants of willingness to pay, Panel B shows high valuation, ceteris paribus, to enroll in a program located in the same region where the student lives, with students willing to pay $14 thousand dollars more to stay in their region of residence. This is consistent with the small fraction of students moving out of their region of residence to study.

The main counterfactual of interest changes tuition prices and measures the change in students' preferences over programs. To this end, the distribution of willingness to pay for different programs is another key economic input. Figure 6 presents the estimated distribution of willingness to pay across programs averaged over residents, net of tuition prices, using estimates from the income-heterogeneous price response model. This figure shows wide dispersion of willingness to pay for programs. Table 9 presents a summary of this distribution, classifying programs into quartiles of different observable characteristics and normalizing the mean across all programs to zero. My estimates show a large willingness to pay for programs that accept students with higher average test scores, fewer public high school graduates, and fewer students from the poorest 40% of the population. The average student is willing to pay between five and ten thousand dollars higher tuition at the most selective programs. The estimates also reveal that students are willing to pay between three to five thousand more for a program with fewer students from public high schools. These comparisons combine programs with different characteristics and selectivity, but reflect the large differences in willingness to pay captured in my estimates and signs that aligned with correlations in the data.

The standard deviation in dollar equivalent utility across students and programs is estimated to be between ten and sixteen thousand dollars. This variation is in the same order of magnitude of the range in posted tuition for one year, but it is larger than the standard deviation in tuition, which was around $1,000 in 2015. This is not surprising given that prices do not clear the market in many programs.

6.2 Model Fit

The model relates student choices to prices and program characteristics, where some of the characteristics capture amenities such as location and others are meant to proxy the quality of the program. However, the main reason for attending college is arguably to boost earnings, something that is not directly captured in the model, as value added is hard to identify, and

it is beyond the purpose of this paper.[28] But to the extent that students reveal this aspect about programs in their choices, we might expect estimates in Table 8 to be aligned with a labor market outcomes.

I assess whether my model captures prestige in the labor market by comparing the predicted ranking of institutions for a given program using my estimates with the ranking of institutions for the same program reported by QuePasa magazine, which asked companies hiring graduates from these programs to rank the different institutions, and the America Economia magazine ranking, which constructs an index program quality based on student quality, teaching quality, research, and accreditation, among others. Table 10 presents the top 10 ranking of willingness to pay for law programs. Out of a total of 89 institutions that host the law program, the top two institutions in the first specification are the elite institutions of the country, and they have not only been used to define the best law major by Zimmerman (2017), but also appear at the top of the QuePasa ranking.

The top-ten ranking produced by both models captures the overall order, and eight to nine out of the ten programs reported in QuePasa as top ten. The ranking my model produces is not what an unrestricted first choice model would capture, nor is it the same if we used stated preferences in rank order lists from the centralized system. As the rest of the columns in Table 10 show, these alternative rankings would have some of the best schools in position 47 or 63.

This fit of the model gives me confidence that the parametric restrictions of the model and omitted variables are not leading to poor predictions about the ordering of programs. Therefore, I proceed with these estimates to perform the counterfactual analysis.

7 Effect of Free Tuition

This section presents the effect of a free tuition policy on low-income students' access to higher education under fixed capacities. Then, I present alternative designs of a financial aid expansion that considers a capacity expansion and means-tested tuition subsidies.

7.1 Crowding Out

Advocates of a free college policy often argue it would equalize access to higher education across income levels.[29] In Chile, this is at the top of the policy discussion, and a government

[28] See Hastings, Neilson and Zimmerman (2013) for causal evidence of wage gains of enrolling in programs at the centralized system.

[29] U.S. Senator Bernie Sanders argues that college is a new minimum for education attainment drawing a parallel between the tuition-free movement and the high school movement, that between 1910 and 1940

elected in 2014 promised to make college free by 2020.[30] Critics of a free tuition policy focus on its high fiscal cost (Espinoza and Urzúa, 2015), on the regressive transfer when there is inequality of access, and on the bigger relative benefits of other policies (e.g. direct subsidies for colleges). The academic and policy discussion have focused on the benefits for prospective new beneficiaries,[31] while ignoring the effect this might have on low-income students who already benefit from means-tested financial aid.

The Chilean financial aid system is currently means-tested and merit-based, with scholarships covering on average 80% of tuition. Therefore, free college for everyone is likely to change enrollment decisions for both low-income and higher-income students. In this context, the existence and importance of crowding out, and whether it will disproportionately affect low-income students is an empirical question that I answer using my estimates, baseline capacities, and simulating the allocation of students to programs using the student proposing deferred acceptance algorithm to find a stable assignment.

A first condition for crowding out to take place is a change in students' preferences after free college is introduced. Panel A of Table 11 shows that indeed demand for college would change after the introduction of free tuition for everyone. Keeping admission cutoffs and capacities fixed at baseline levels, the introduction of free tuition would lead to a large excess of demand. This would require a capacity expansion ranging 37 to 58% for universities to absorb excess demand without changing their admission criteria. The equilibrium concept of stability for the higher education market introduced in subsection 5.1 and used in the example of subsection 4 implies that admission cutoffs would need to adjust in order to equate demand and capacities.

The distributive consequence of free tuition depends on the socio-economic status of marginally admitted students and the relation between income and admission test scores. Figure 7 shows the socio-economic composition of students marginally admitted at university programs. In the 2015, students who are just marginally admitted have lower socio-economic status than students further above the admission cutoff. While 20% of those students just above the admissions cutoff come from the poorest 24%, only 7% come from the wealthiest 20%. This implies that when cutoffs adjust to the new equilibrium, low-income students will likely be more affected. Figure 8 shows that the density of the average Mathematics-Language admission score for the poorest 20% is considerably below that of the wealthiest 20%. This figure also presents the change in the median admission cutoff of universities in the

increased enrollment and funding for secondary education at a time when only a small fraction of people graduated with a high school diploma.

[30] This is unlikely to happen, but the promise was source of a legislative agenda in that direction.

[31] Part of the literature also studies the effect of financial aid on tuition prices (e.g. Cellini and Goldin (2014)).

same scale, suggesting that a larger mass of lower-income students are affected by increased competition. Indeed, the increase in admission scores puts a larger mass of lower-income students below the admission cutoff compared to their wealthiest counterparts.

Panels A and B of Table 12 show the change on enrollment for different income quintiles and preference estimates. Across estimates and types of institutions, students in the poorest 20% of the population would experience a decrease in enrollment of 10% in favor of wealthier students, who would increase their enrollment. Similarly, the second and third income quintile, who were already benefiting from means-tested financial aid, would be displaced from enrolling in college. For these two income quintiles, negative effects are especially large at more selective programs in the centralized admission system.

Panels A and B of Table 13 show the change in dollar equivalent utility (with and without prices) for both estimated models and the change in average tuition and scholarship awarded for different demographic groups. Both models show negative welfare effects for low-income students, with modest welfare gains for wealthier students in the income-heterogeneous price coefficient model. The negative welfare effects are explained by two forces. First, as highlighted in the stylized model in subsection 4, students whose behavior changes with financial aid are those with the lowest valuation. This means that the (net of price) utility of some of the students that switch could be negative, and that is the case in Panel A. Second, displacements in the admission process create further rejection chains down students' preference lists. Indeed, students who are first displaced from a selective program will apply next to their next preferred alternative and potentially displace another student in this process. Students losing their seat will experience a negative welfare effect that aggregates to the results presented in Table 13. An exception in this analysis are students in the highest quartile of test scores, who experience an average gain in both models, potentially explained by their larger choice sets, which enable them to choose among most programs, and a minimum risk of being displaced by other students. This table also reveals that among students who enroll in both scenarios, low-income students are displaced to less expensive programs. And while everyone who enrolls receives a higher scholarship, the negative welfare of displacement to less desirable programs and displacement out of college outweigh the larger financial aid benefits.

The welfare analysis is based on the assumption that preferences are quasilinear in prices. This assumption is reasonable if financial aid has negligible income effects. This is a plausible approximation given the existence of a state guaranteed loan, which, as Solis (2017) shows, eases credit constraints, and the fact that financial aid is a small transfer compared to the overall stream of wealth produced by attending college.

7.2 Alternatives

Supply Expansion

Programs' capacities might adjust in the longer-run after free tuition is introduced. It is not clear whether a free tuition plan would allow programs to expand, Londoño-Vélez, Rodríguez and Sánchez (2017) suggest that the introduction of a large but highly means-tested scholarship in Colombia increased supply at eligible institutions, while Murphy, Scott-Clayton and Wyness (2017a) argue that England's free college era showed that free tuition provided "insufficient funding to support the 'massification' of higher education." Similarly, Bound and Turner (2007) show that faced with increased demand for higher education due to larger cohorts, colleges did not adjust capacities due to lack of non-tuition funds. In Chile, evidence based on past financial aid expansions suggests that several programs decreased their capacities. Given the uncertainty in programs' response to free tuition, I evaluate the effect of free tuition together with different capacity expansions. I view this exercise as a way to determine the importance of crowding out in a different metric, and as a potential policy to avoid it.

For simplicity, I evaluate how enrollment of students in the poorest 20% would change after free tuition is implemented with a capacity expansion of 0 to 20%, with all programs expanding by the same percentage. I focus my attention on low-income students because they are crowded out of college, and they are the main motivation for the existence of financial aid in the first place. The flat dashed line in Figure 9 shows the baseline enrollment rate for the poorest 20%, while the solid line shows their enrollment rate after free tuition is implemented with the different levels of capacity expansion. We see that there is a supply expansion level, around 10%, that would keep enrollment rate at baseline level for the poorest, even after making college free.

The expansion in capacities required to ameliorate crowding out have not been seen before among traditional programs in the centralized system, which in the last 9 years expanded only by 5%. On the other hand, low-quality programs and institutions have expanded through the creation of new programs in the past decade.[32] To the extent that we worry about the quality of higher education that low-income students attend, and about poor students that at baseline were enrolling, the results above should raise concerns for policy makers. A careful design of a capacity expansion would be necessary to ensure that low-income students are not displaced to lower-quality programs.

[32] Bordon et al. (2016) study this process in detail, showing how the expansion reduced quality among programs.

Means-Testing

Another common policy is to provide means-tested financial aid. This is the way the Chilean system has expanded financial aid in the past. To isolate this aspect of the design of financial aid I keep capacities fixed. I adopt a stylized scholarship scheme where the tuition that student i faces at program j is $\text{Tuition}_{ij} = \gamma\alpha(I_i)\text{Tuition}_j$, where I_i is student i's income, Tuition_j is the full tuition and γ is a free parameter that indexes means-testing. $\alpha(I_i)$ corresponds to the schedule:

$$\alpha(I_i) = \begin{cases} 0 & \text{if } I_i \leq \underline{I} \\ \frac{I_i - \underline{I}}{\overline{I} - \underline{I}} & \text{if } \underline{I} \leq I_i \leq \overline{I} \\ 1 & \text{if } \underline{I} \leq I_i \end{cases} \tag{16}$$

where $\underline{I}$ is the income threshold for the first income quintile, and $\overline{I}$ is the income threshold for the fifth income quintile. In all scenarios, the first income quintile receives a full scholarship, and there are a range of scenarios where wealthier students get more or less financial aid. This is consistent with the type of policies observed in reality, where the poorest students get at least as much financial aid as the rest.

I evaluate a range of means-testing levels in the benefit, γ, that go between 0 and 1. Figure 10 presents these different schedules. When $\gamma = 0$, all students get a free tuition, while $\gamma = 1$ corresponds to the case where the fifth income quintile does not get any financial aid and the rest of the students get a partial subsidy that decreases with income, starting from a full scholarship for all students in the poorest 20%.

Figure 11 shows the enrollment rate of students in the poorest 20% at university programs. Low targeting levels lead to higher competition for the same seats and lower enrollment among students in the poorest 20%. I find that for $\gamma \approx .5$, which corresponds to the case where the richest 20% gets a scholarship worth half tuition, low-income students enroll at a similar rate to the current system in Chile. Any policy that is less targeted than that would lead to crowding out. This exercise shows that in the short run, maintaining some level of means-testing in the amount of the benefits can alleviate the crowding out consequences on low-income students. This is in fact the way that the Chilean government is progressing towards free tuition in 2017.

8 Conclusion

Many countries are discussing or considering making college free or expanding financial aid eligibility. While the effect that a financial aid package has on any given student is well understood, it is unclear how free college would affect low-income students who already benefit from financial aid. Larger financial aid subsidies might benefit low-income students, but less targeted aid is likely to motivate newly eligible students to change their college application behavior, potentially increasing competition for limited seats and crowding out some students. Depending on the distribution of test scores and income, and the socio-economic status of students who are being marginally admitted, this policy could have distributive consequences in the access to higher education. This paper combines rich administrative data from Chile, where the current government promised to make college free by 2020, with a simple structural model to quantify how important crowding out could be and to demonstrate the importance of design in financial aid policies.

Evidence from a difference-in-differences strategy using past financial aid expansions in Chile shows that programs that used to attract more students with scholarships experienced an increase in their admission cutoffs and a drop in the share of low-income students after the eligibility for scholarships began expanding in 2012. On the other hand, a regression discontinuity strategy on scholarship eligibility shows that financial aid has an important intensive and extensive margin effect on enrollment. These quasi-experimental results show that crowding out is a relevant policy matter that could introduce unintended negative consequences to free college tuition.

I exploit a regression discontinuity design in scholarship eligibility to identify the price elasticity in demand estimation. This is the key parameter to study financial aid expansions. I prove that the quasi-experimental variation in tuition identifies the price coefficients in a general random utility model. Additionally, I leverage the tradition of admitting students based only on high school GPA and test scores, and the existence of a large centralized admission system, to assume that the observed enrollment decisions are students' preferred programs among all programs that would admit them. This allows me to estimate a flexible model of students' preferences for college. I use the estimates to show how many low-income students would be crowded out by a free college policy. I find that 20% of low-income students enrolled at the baseline would be crowded out under fixed college capacities, and that the enrollment rate of low-income students would drop by 10%.

These findings raise questions about the design of financial aid policies that intend to help low-income students while extending financial aid benefits. I show that free tuition would need to be accompanied by a capacity expansion of 10% in university programs in order to

keep low-income students' enrollment rate at its baseline level, and that capacity would need to expand by more than 20% to avoid displacing low-income students who were enrolled in the baseline. It is unclear that institutions will be willing or able to expand their capacities by that much, so policy makers should incorporate capacities as a key aspect of the design of financial aid expansions. On the other hand, even if capacities are fixed, policy makers could introduce universal financial aid without hurting low-income students' enrollment rates by means testing the amount of aid each student receives. These results suggest that free college might hurt low-income students' enrollment opportunities if designed incorrectly.

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Tables and Figures

Table 1: Program Characteristics by Type of Higher Education Institution in 2015

Higher Education Institution Type:	Vocational Institutions		Universities			All
Admission System:	Decentralized Admission		Decentralized Admission	Centralized Admission		
	CFT	IP		CRUCH	Private not-CRUCH	
A. Institutions and Programs						
Number of Institutions	46	40	25	25	8	144
Number of Programs	1,596	3,061	1,494	1,386	462	7,999
Average Annual Tuition (in thousand US dollars)	$2.02	$2.05	$3.70	$4.25	$6.02	$3.10
B. Enrollment						
Total Enrollment	62,397	122,330	48,619	71,669	28,185	333,200
Percentage just Graduating High School	23%	21%	32%	49%	29%	32%
Percentage of Students who Took Admission Test	74%	74%	88%	95%	96%	82%
Average Math-Language score of Last Admitted Student	298	301	370	467	462	360

Notes: Decentralized admission refers to institutions that do not participate of the centralized match described in section 2. The number of programs is restricted to having observable characteristics. National admission test is used by selective institutions, and it is graded between 110 and 850 points with a standard deviation of 110 and mean of 500. Program characteristics are enrollment-weighted averages.

Table 2: Scholarships for University Programs, 2015

Name of Scholarship	Eligible Institutions	Amount	Eligible Students
Scholarship 1: "Beca Bicentenario"	Only CRUCH universities (Group of 25 universities)	Reference Tuition	500 points Average Math and Language – 70% poorest students
Scholarship 2: "Beca Juan Gomez Millas"	Rest of Accredited Universities	Same amount at any major ∼2,000 USD <Reference Tuition	500 Average Math and Language – 70% poorest students

Notes: Reference tuition is around 80% of the posted tuition, but varies across programs. Scholarships cover same amount for the duration of the program.

Table 3: Student Characteristics in 2015

	N=171,011	
	Mean	Std
Average Math and Language Test Score	494	102
GPA	572	111
Enrollment Status		
Any program	0.61	0.49
University	0.38	0.45
Vocational	0.24	0.36
Income Quintiles		
1st (20% Poorest)	0.21	0.41
2nd	0.20	0.40
3rd	0.14	0.35
4rth	0.11	0.31
5th (20% Richest)	0.08	0.26
No quintile (No financial aid application)	0.27	0.44
Financial Aid		
Has Scholarship to attend University	0.20	0.40
Has Government Guaranteed Loan	0.17	0.33
Type of High School		
Public	0.31	0.46
Voucher	0.58	0.49
Private	0.11	0.31
Mother Education		
Incomplete High School or no HS	0.37	0.48
Complete High School	0.35	0.48
At least some college studies	0.28	0.45
Mother Head of Household	0.35	0.48

Notes: This table shows characteristics of students just graduating from high school in 2015 that take the admission test score (PSU). GPA is converted to the same scale of admission test score (mean of 500; standard deviation of 110).

Table 4: Regression Discontinuity Results for Income-Eligible Students

	Enrollment at Programs:		
	Eligible	All	Ineligible
	(1)	(2)	(3)
1(Average Math-Language Score ≥ Eligibility Cutoff)	0.095***	0.065***	-0.031***
	(0.012)	(0.009)	(0.009)
Mean below cutoff	0.28	0.69	0.34
Observations	31,808	45,020	31,737

Notes: The sample corresponds to first-time PSU takers among the poorest 60% of the population in 2015. Columns (1)-(3) report results of equation (1) for the respective outcome, using optimal bandwidths computed for each outcome. Means below the cutoff for non-parametric specifications are computed using data 0.2 standard deviations of the running variable below the cutoff, while parametric specifications use the estimated constant. * significant at 10%; ** significant at 5% ; *** significant at 1%.

Table 5: Regression Discontinuity Results by Income Quintile

	Family Income Quintile:			
	1st (20% Poorest)	2nd	3rd	5th (Placebo)
A. Enrollment at Eligible Programs	0.077***	0.100***	0.109***	0.050
1(Average Math-Language Score ≥ Eligibility Cutoff)	(0.019)	(0.019)	(0.022)	(0.034)
Mean below cutoff	0.27	0.30	0.29	0.34
B. Enrollment in All Programs	0.061***	0.056***	0.072***	0.028
1(Average Math-Language Score ≥ Eligibility Cutoff)	(0.017)	(0.016)	(0.018)	(0.031)
Mean below cutoff	0.63	0.73	0.72	0.65
C. Enrollment at Ineligible Programs				
1(Average Math-Language Score ≥ Eligibility Cutoff)	-0.012	-0.044**	0.024	-0.022
	(0.017)	(0.018)	(0.024)	(0.030)
Mean below cutoff	0.36	0.44	0.43	0.31
Observations	36,475	33,568	23,933	12,862

Notes: The sample corresponds to first-time PSU takers in 2015. Each estimate reports non-parametric (IK) results for the respective outcome and quintile. Optimal bandwidths computed for each outcome-quintile combination. Means below the cutoff are computed using data 0.2 standard deviations of the running variable below the cutoff. * significant at 10%; ** significant at 5% ; *** significant at 1%.

Table 6: Difference-in-Difference estimates for Crowding Out, Admission Cutoffs and Enrollment

Dep. Variable:	Share of Students in Poorest 40%			Minimum Average Math-Language			Enrollment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(t>2011) x Share of Students	-0.226***	-0.292***	-0.292***	232***	232***	232***	-34***	-34***	-34***
in poorest 40%	(0.014)	(0.015)	(0.012)	(29.6)	(20.4)	(25.8)	(7.4)	(1.8)	(6.0)
Number of Observations	7,320	7,320	7,320	6,588	6,588	6,588	7,320	7,320	7,320
Number of Universities	25	25	25	25	25	25	25	25	25
Number of Programs	732	732	732				732	732	732
Number of Years	10	10	10	10	10	10	10	10	10
Year Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Program Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Clustered Standard Errors	No	No	Yes	No	No	Yes	No	No	Yes
One Standard Dev. Effect	-0.036	-0.047	-0.047	37.2	37.2	37.2	-5.5	-5.5	-5.5
Summary of Dependent Var.		0.504 (0.169)			528 (52.2)			55 (46.9)	

Notes: This table shows the main coefficient of difference-in-differences regressions at the program level with fixed effects and clustered standard errors at that level when indicated. I use the minimum average Language-Mathematics, that has standard deviation of 110 and mean 500, because the weights per program change across years. The average share of students in the poorest 40% income eligible pre-2012 financial aid expansion defines the more exposed program to posterior financial aid expansions. The one standard deviation effect corresponds to the main coefficient in each column multiplied by 0.16 which is the standard deviation of the share of students in the poorest 40% pre-2012. Varying number of observations reflects missing data for the minimum score among enrolled students. Standard errors in parenthesis. * significant at 10%; ** significant at 5% ; *** significant at 1%.

Table 7: Average Price Elasticity by Income Quintile

	Common Price Coefficient Model (1)	Income-heterogeneous Price Coefficient Model (2)
Poorest 20%	-0.86	-0.48
2nd Income Quintile	-0.89	-0.72
3rd Income Quintile	-0.90	-0.97
4th Income Quintile	-0.91	-1.15
Richest 20%	-0.94	-1.33

Notes: This table shows the average elasticity across students and programs evaluated at the full tuition price for each estimated model.

Table 8: Preference Estimates

Specification:	Common Price Coefficient Model (1)		Income-heterogeneous Price Coefficient Model (2)			
			Poorest 20%		Richest 20%	
A. Preference for Programs (Units of standard deviation)						
Share of students from Public HS						
Main Effect	-6.666***	(0.696)	-13.984**	(6.851)	-5.42***	(1.091)
Poorest 40%	0.447***	(0.054)	2.597**	(1.322)	1.007***	(0.233)
Share of students from Quintiles 1 or 2						
Main Effect	-6.059***	(0.656)	-12.197**	(5.996)	-4.728***	(0.971)
Poorest 40%	-0.175***	(0.046)	1.251*	(0.704)	0.485***	(0.149)
Public High School	0.308***	(0.118)	3.843**	(1.936)	1.49***	(0.318)
Voucher High School	0.876***	(0.129)	5.224**	(2.612)	2.025***	(0.426)
Average Math-Language Score of students						
Main Effect	2.557***	(0.551)	-1.302	(1.332)	-0.505	(0.464)
Poorest 40%	-3.814***	(0.327)	1.251*	(0.704)	0.485***	(0.149)
Student Test Score	-4.491	(3.359)	0.257	(0.955)	0.1	(0.37)
Random Coefficient			0.014	(0.416)	0.005	(0.16)
Size						
Main Effect	-6.828***	(1.214)	-13.434*	(6.955)	-5.207***	(1.363)
B. Preference for Programs						
Same Region	14.557***	(1.211)	26.805**	(13.01)	10.39***	(1.968)
STEM						
Main Effect	-2.021***	(0.457)	-3.344*	(1.907)	-1.296***	(0.459)
Public HS student	-0.06	(0.095)	-1.983**	(0.944)	-0.769***	(0.146)

Notes: Detailed estimates in Appendix. Estimates monetized in thousand dollars (normalize price coefficient to 1). Panel A presents the dollar equivalent for a 1 standard deviation change in a program characteristic. All columns include interactions described at the end of subsection 4.2. All specifications normalize the mean utility from a program with zeros on all characteristics to 0. Optimization and estimation details described in an appendix. Standard errors in parenthesis. * significant at 10%; ** significant at 5% ; *** significant at 1%

Table 9: Estimated Utility Distribution in Dollar Equivalent

		Common Price Coefficient Model (1)	Income-heterogeneous Price Coefficient Model (2)
	N	Stat	Stat
A. Means in Category			
Share of students from Public HS			
Lowest Quartile	601	$644	$28
Second Quartile	584	$826	$369
Third Quartile	597	-$464	-$1,143
Highest Quartile	588	-$3,696	-$5,888
Share of students from Quintiles 1 or 2			
Lowest Quartile	594	-$2,254	-$4,653
Second Quartile	598	-$266	-$787
Third Quartile	586	$313	-$11
Highest Quartile	592	-$345	-$770
Average Math-Language Score of students			
Lowest Quartile	593	-$2,773	-$5,498
Second Quartile	592	-$918	-$1,903
Third Quartile	593	$2,857	$4,181
Highest Quartile	592	$5,156	$10,135
Size			
Lowest Quartile	611	-$3,721	-$5,736
Second Quartile	610	-$1,515	-$3,305
Third Quartile	559	$1,203	$830
Highest Quartile	590	$3,395	$4,567
STEM Program	629	-$793	-$1,219
Overall Std. Dev.	2370	$9,651	$16,855

Notes: Utilities net of tuition are monetized in dollars and normalized to an overall mean of zero across students and programs.

Table 10: Ranking of Law Programs

	Willingness to Pay Ranking of Specification:		Magazine Ranking:		Alternative Models:	
University	Common Price Coefficient Model	Income-heterogeneous Price Coefficient Model	QuePasa	America Economia	Size	#Ranked First
Pontificia Universidad Catolica de Chile	1	2	1	1	2	2
Universidad de Chile	2	4	2	3	1	1
Pontificia Universidad Catolica de Valparaiso	3	1	4	6	47	11
Universidad de los Andes	4	5	8	4	6	47
Universidad del Desarrollo	5	9	10		11	3
Universidad Diego Portales	6	3	7	5	4	16
Universidad Catolica del Norte	7	14			20	6
Universidad de Valparaiso	8	8	9	7	28	8
Universidad de Tarapaca	9	16			14	26
Universidad de Atacama	10	24			3	63
Universidad de Concepcion	11	6	3	2	16	13
Universidad Alberto Hurtado	21	7			17	9
Universidad de Talca	16	10	5	9	21	4

Notes: This table presents rankings of universities for the law major according to the average willingness to pay from the two specifications estimated, two rankings from magazines and two alternative variables. QuePasa and America Economia produce rankings similar to the US News ranking. Size refers to the number of enrolled students, and #Ranked First refers to the number of students who rank programs first in the centralized admission process. There are a total of 89 institutions that teach the law major in 2015.

Table 11: Excess of Demand with Free Tuition, Capacities and Admission Cutoffs at Baseline Level

	Type of Program			
	All	University	Centralized System	Vocational
A. Percentage Excess of Demand				
Common Price Coefficient Model	47%	58%	44%	28%
Income-heterogeneous Price Coefficient Model	35%	37%	25%	31%
B. Program Characteristics				
Share of Students Enrolled in Baseline	100%	64%	40%	34%
Number of Programs	2,370	2,361	1,287	-

Notes: This table presents the percentage excess of demand over baseline capacity after introducing free tuition, assuming that admission cutoffs and capacity remain at baseline levels from year 2015. Admission cutoffs are simulated for the baseline equilibrium using estimates of preferences for the respective model. Panel A uses estimates from each of the two models considered in estimation, while Panel B shows basic descriptive of the baseline. Centralized system are the group of university programs that admit students using a coordinated system. The number of vocational programs is omitted as I group them in nine categories for estimation.

Table 12: Baseline and Percentage Change in Enrollment by Institution and Income Quintile after Free Tuition Introduction

	All Programs		University		Centralized System	
	Baseline	Change with Free College	Baseline	Change with Free College	Baseline	Change with Free College
A. Common Price Coefficient Model						
Poorest 20%	0.57	-10%	0.27	-11%	0.15	-13%
2nd Income Quintile	0.78	0%	0.44	-11%	0.27	-20%
3rd Income Quintile	0.73	-5%	0.46	-6%	0.29	-11%
4th Income Quintile	0.69	8%	0.50	9%	0.32	11%
Richest 20%	0.69	17%	0.59	15%	0.38	17%
B. Income-heterogeneous Price Coefficient Model						
Poorest 20%	0.56	-7%	0.27	-12%	0.15	-13%
2nd Income Quintile	0.72	-2%	0.40	-8%	0.25	-12%
3rd Income Quintile	0.72	3%	0.46	-5%	0.29	-12%
4th Income Quintile	0.71	11%	0.53	6%	0.34	7%
Richest 20%	0.72	18%	0.62	11%	0.40	13%

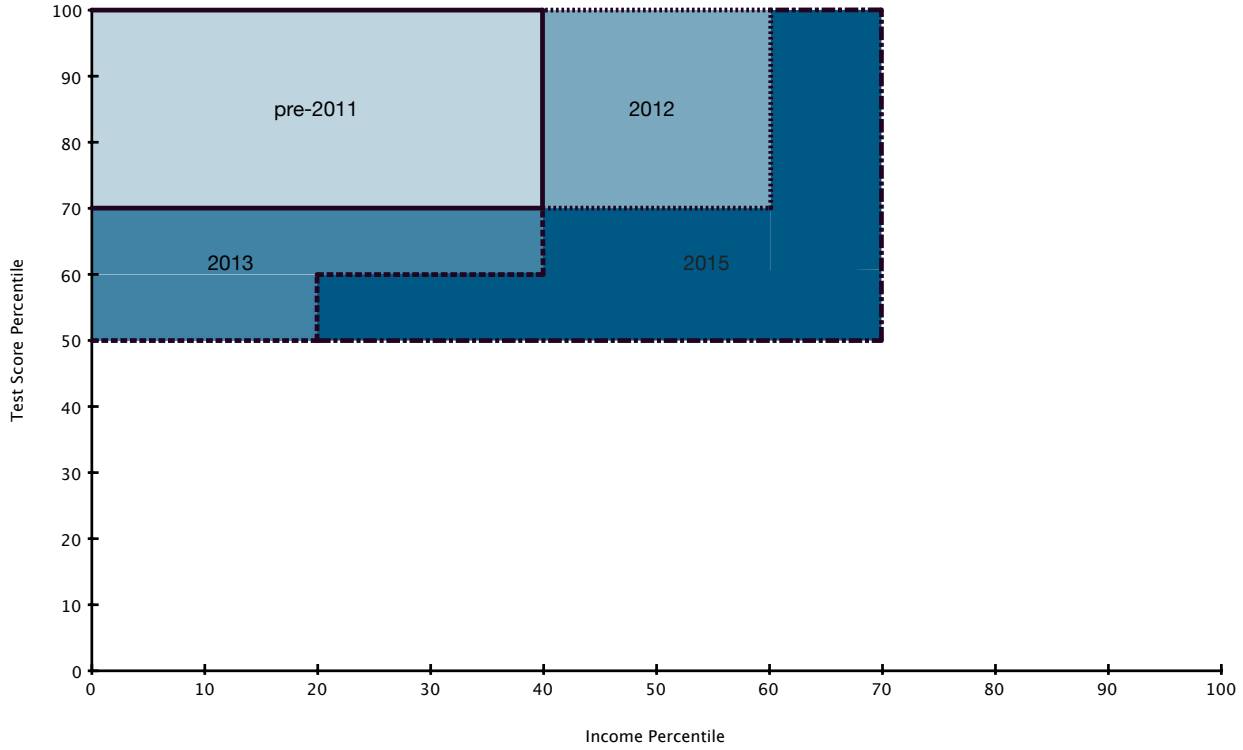
Notes: This table presents the change in average enrollment for different income groups at different institutions before and after a free tuition policy. Each panel presents the same figures for the two models estimated. Simulations hold capacities fixed at baseline levels of 2015.

Table 13: Welfare Consequences of Tuition Free College

	Change in average:			
	Utility	Utility Net of Price	Sticker Tuition	Received Scholarship
A. Common Price Coefficient Model				
Family Income				
Poorest Quintile	-$3,396	-$1,180	-$567	$1,137
Second Quintile	-$4,586	-$1,454	-$243	$1,458
Third Quintile	-$2,994	-$1,109	-$524	$1,274
Fourth Quintile	-$1,247	-$776	$630	$2,736
Richest Quintile	-$96	-$490	$1,460	$3,484
Test Scores				
Lowest Quartile	-$8,533	-$2,485	-$2,184	$24
Top Quartile	$1,955	$178	$3,328	$4,515
B. Income-heterogeneous Price Coefficient Model				
Family Income				
Poorest Quintile	-$6,530	-$1,078	-$506	$1,271
Second Quintile	-$3,684	-$990	-$323	$1,379
Third Quintile	-$1,461	-$778	-$25	$1,629
Fourth Quintile	$404	-$572	$675	$3,070
Richest Quintile	$1,486	-$332	$1,204	$3,832
Test Scores				
Lowest Quartile	-$10,980	-$2,178	-$2,160	$34
Top Quartile	$5,480	$614	$2,509	$5,038

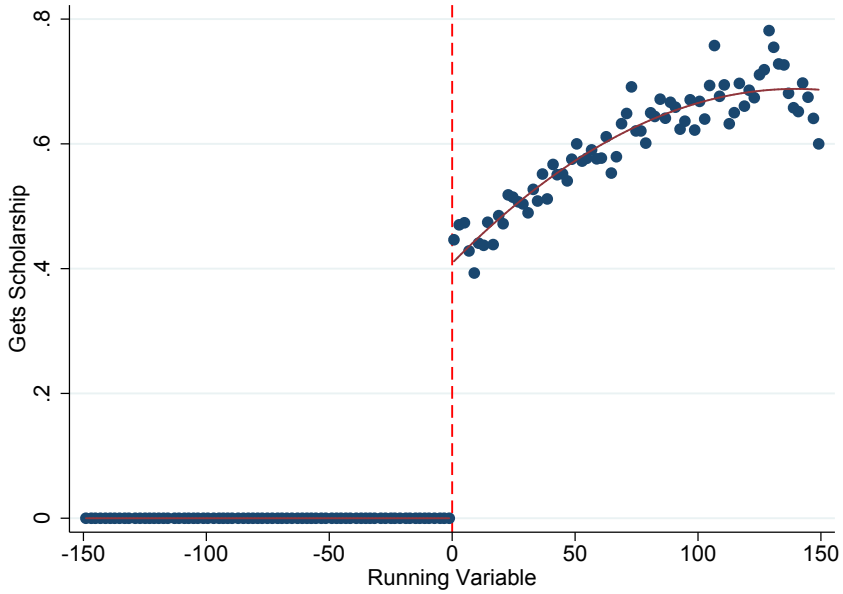
Notes: This table compares the average of the variable in each column for the free tuition case and the baseline. Utilities are expressed in dollar equivalent.

Figure 1: Changes in Scholarship Eligibility Criteria between 2011 and 2015

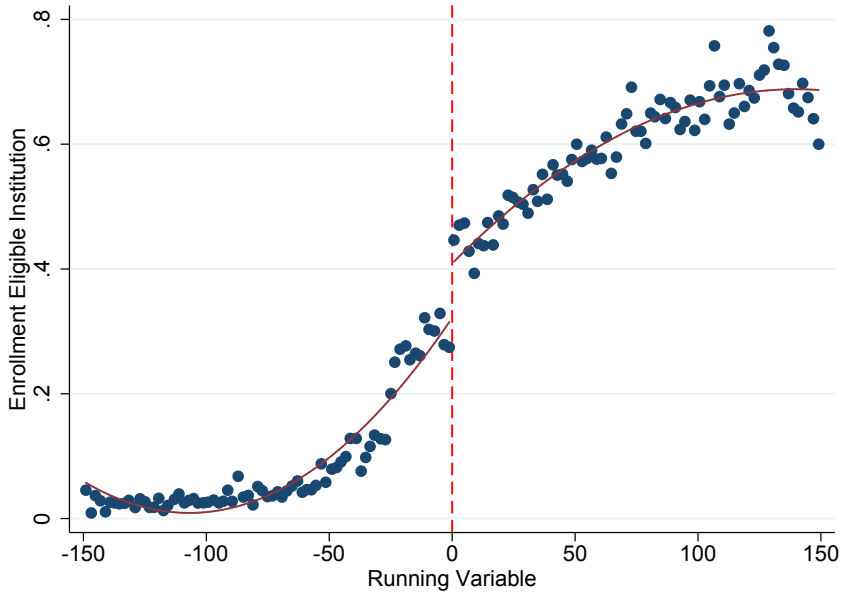


Notes: Test score eligibility is based on the average of the mathematics and language scores in the admission test. I transformed the score to percentiles.

Figure 2: Average Scholarship status and Enrollment at eligible institutions



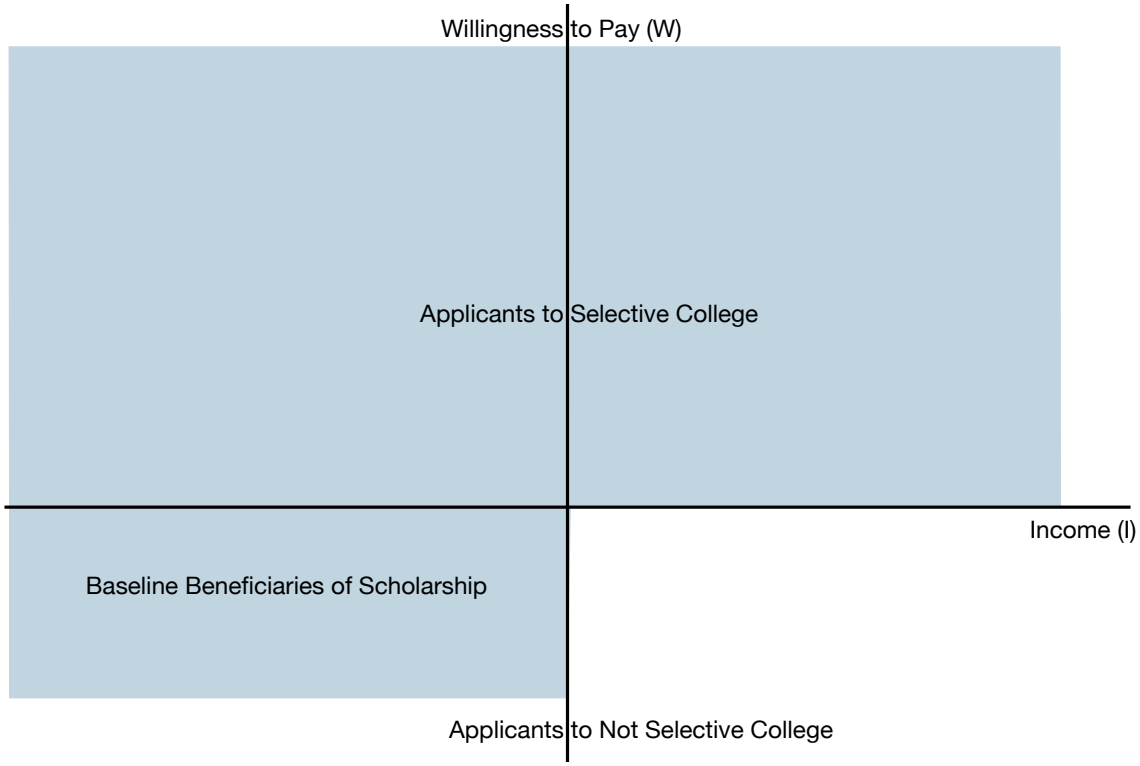
(a) Scholarship Assignment



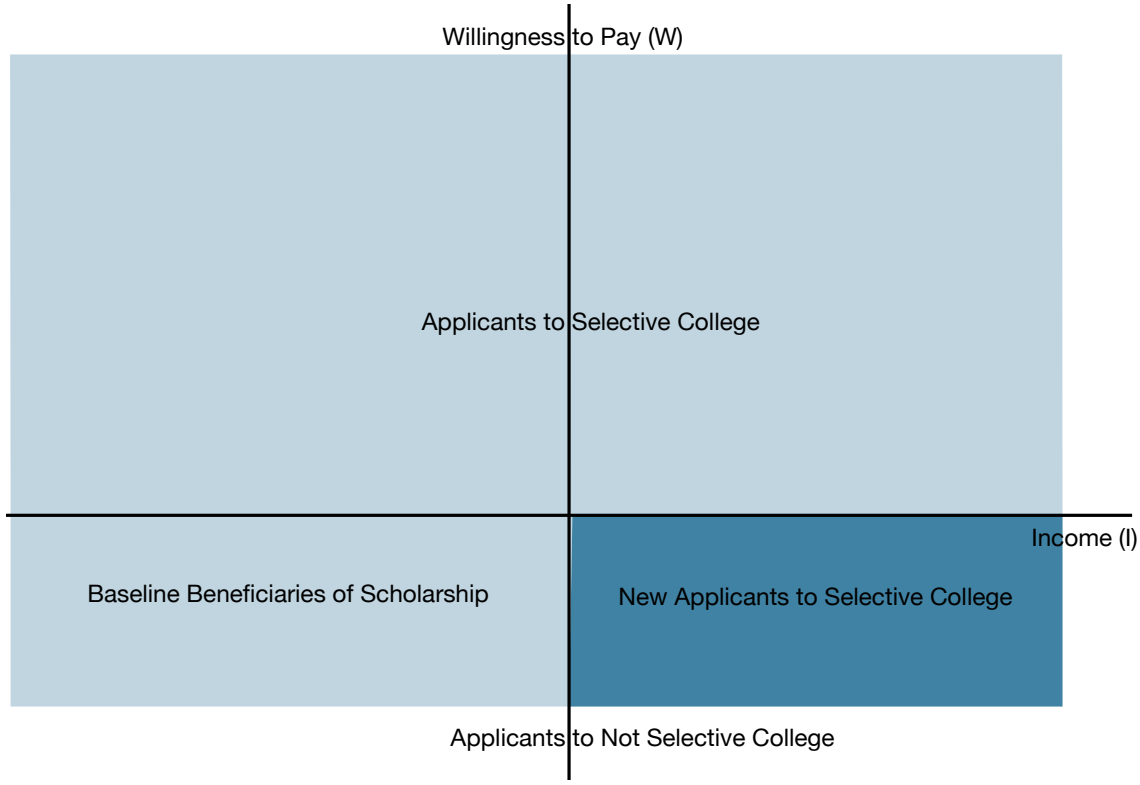
(b) Enrollment at Eligible Institutions

Notes: The running variable is the average mathematics and language score. Both figures use the sample of students among the poorest 60% in 2015 and plot a scatter of binned averages using 2 points of the re-centered running variable each. The top panel shows the proportion of students with one of the two scholarships used in this paper. The bottom figure shows the proportion of students enrolled at an eligible institution as a function of the running variable, and a 2nd order polynomial fit on both sides of the cutoff.

Figure 3: Graphical Representation of Stylized Example in Space (I, W)

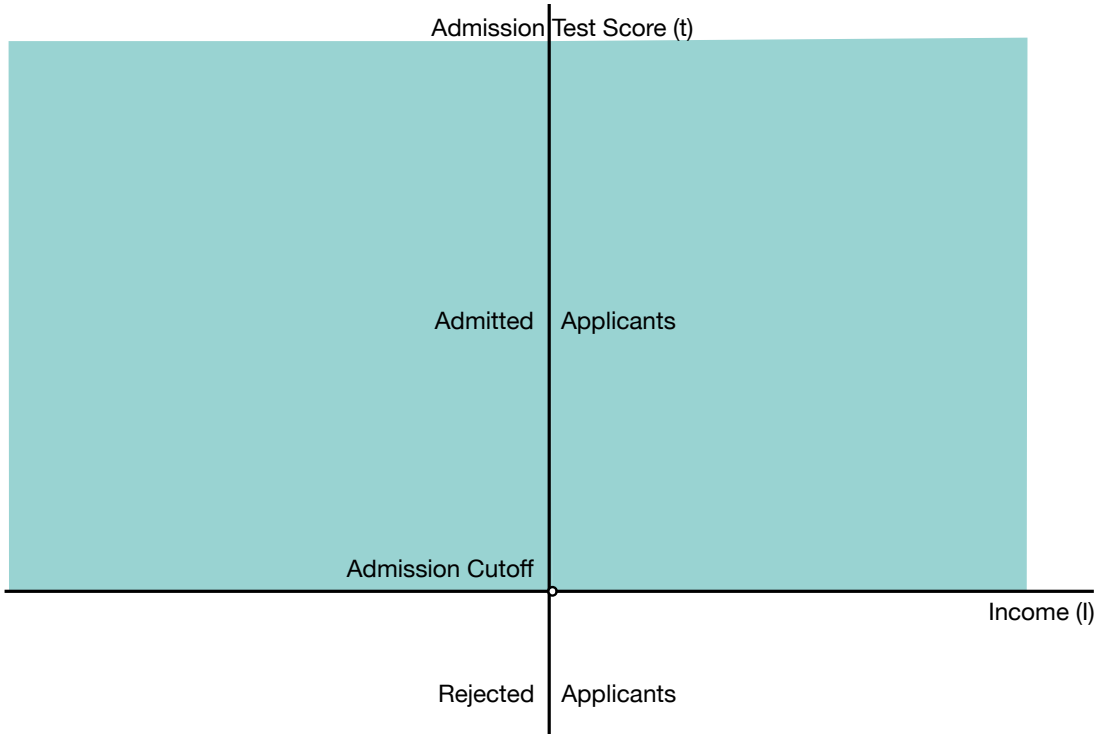


(a) Applicant Population at Baseline

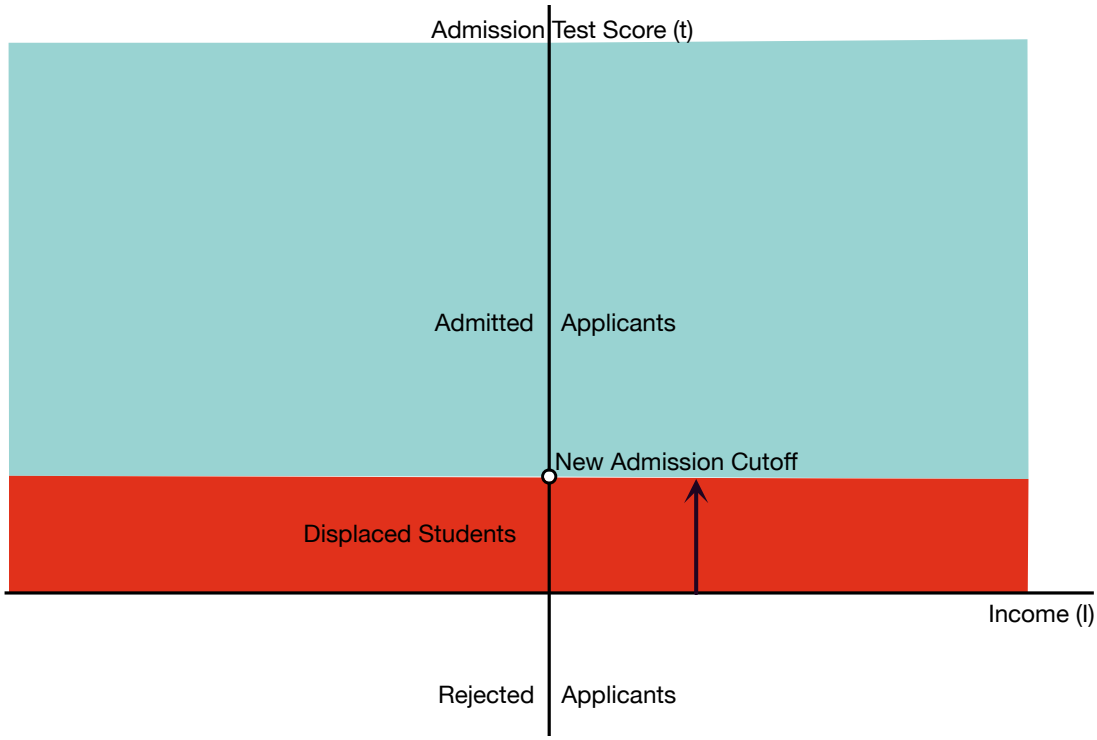


(b) Applicant Population with Tuition Free College

Figure 4: Graphical Representation of Stylized Example in Space (I, t)



(a) Admitted Population to Selective College in Baseline



(b) Admitted Population to Selective College with Tuition Free College

Figure 5: Means-Testing Design of Scholarship

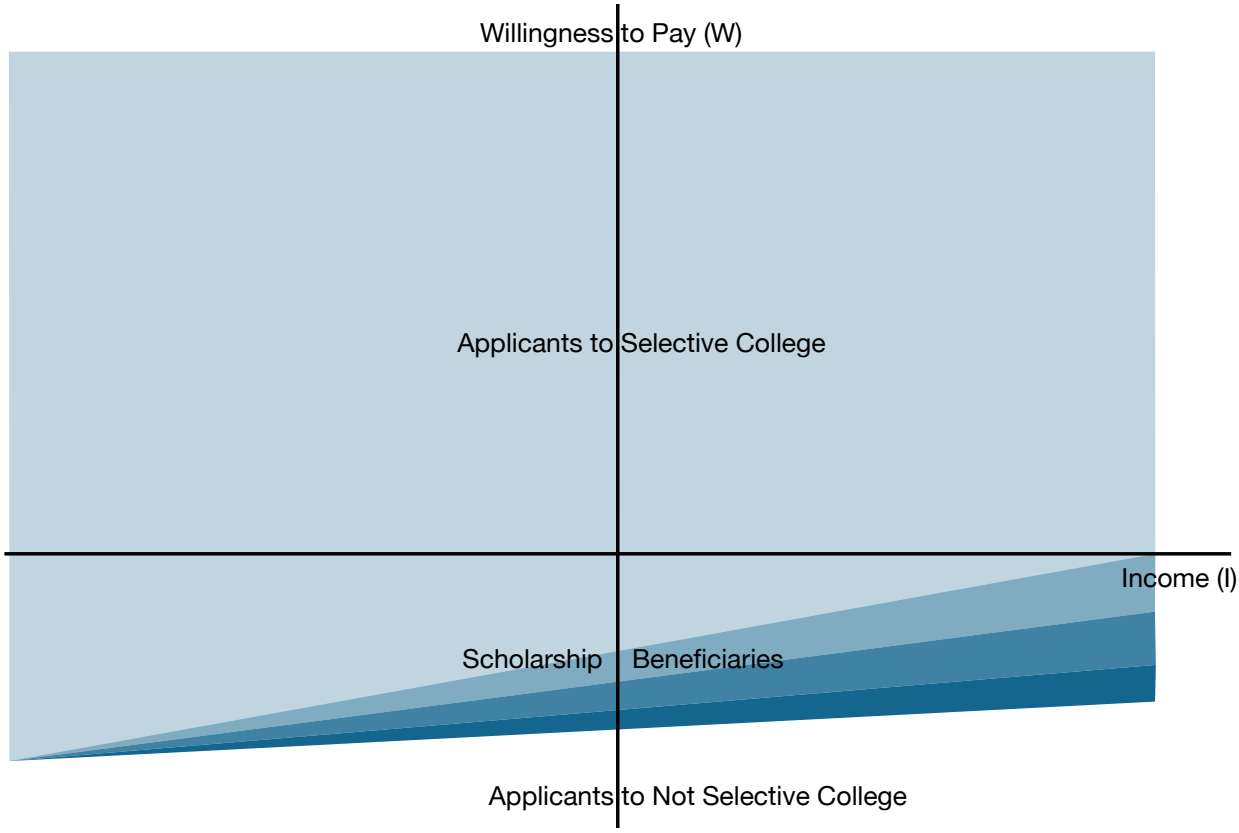
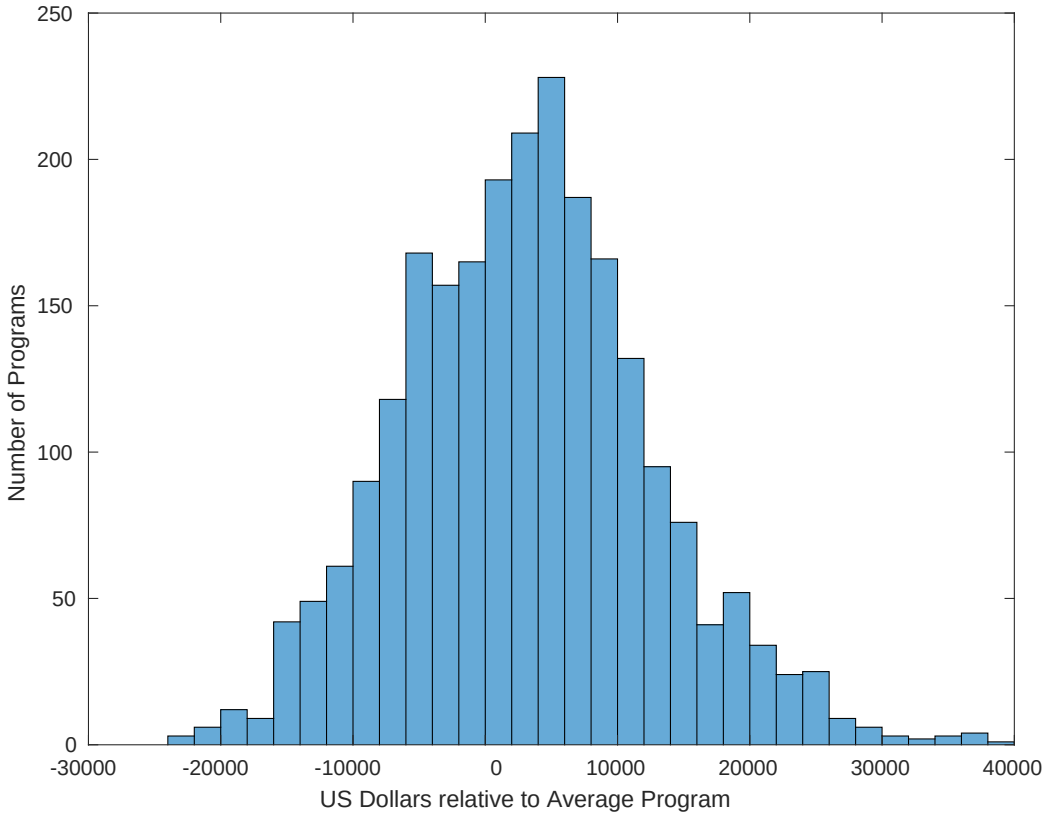
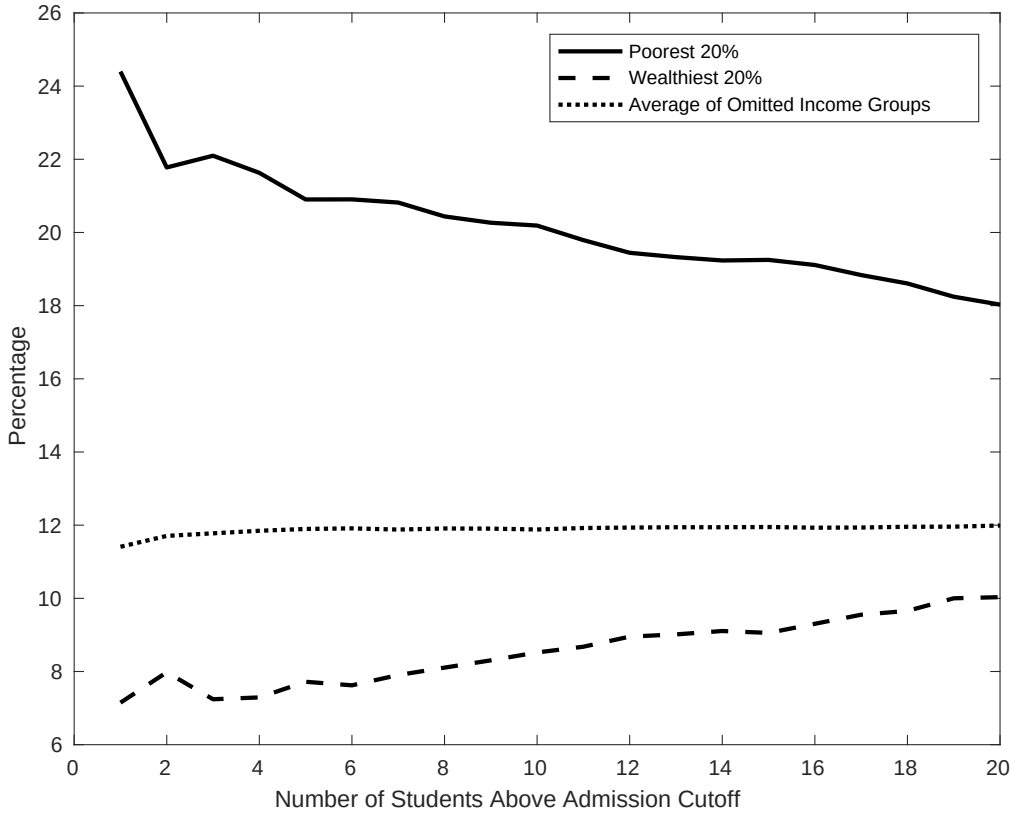


Figure 6: Estimated Distribution of Program Utility



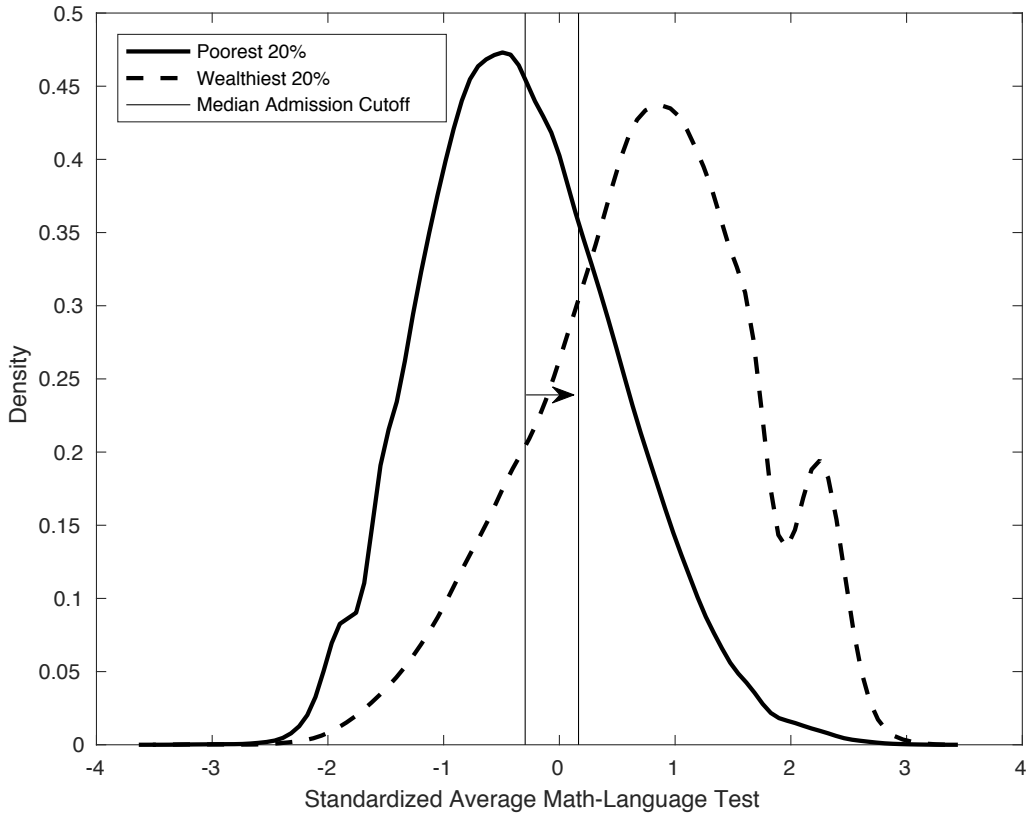
Notes: Estimated distribution of mean utility, net of tuition, across programs monetized in dollars with the mean utility normalized to zero. This figure uses estimates from the specifications with income-heterogeneous price coefficient.

Figure 7: Socio-economic composition of marginal students at 4-year programs' admissions



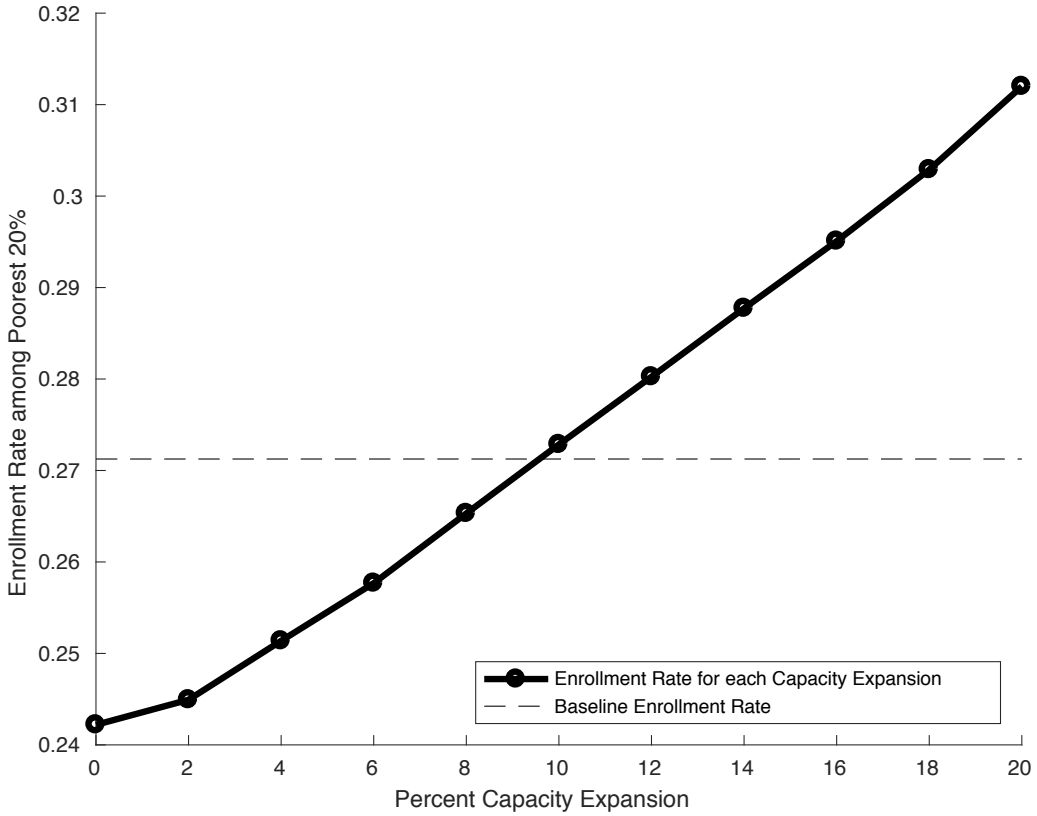
Notes: This figure shows the percentage of students in the poorest 20%, wealthiest 20% and rest of students for different number of students groups above the admission cutoffs at university in the baseline of 2015.

Figure 8: Distribution of Average Mathematics-Language Admission Scores and Change in Median Admission Cutoff



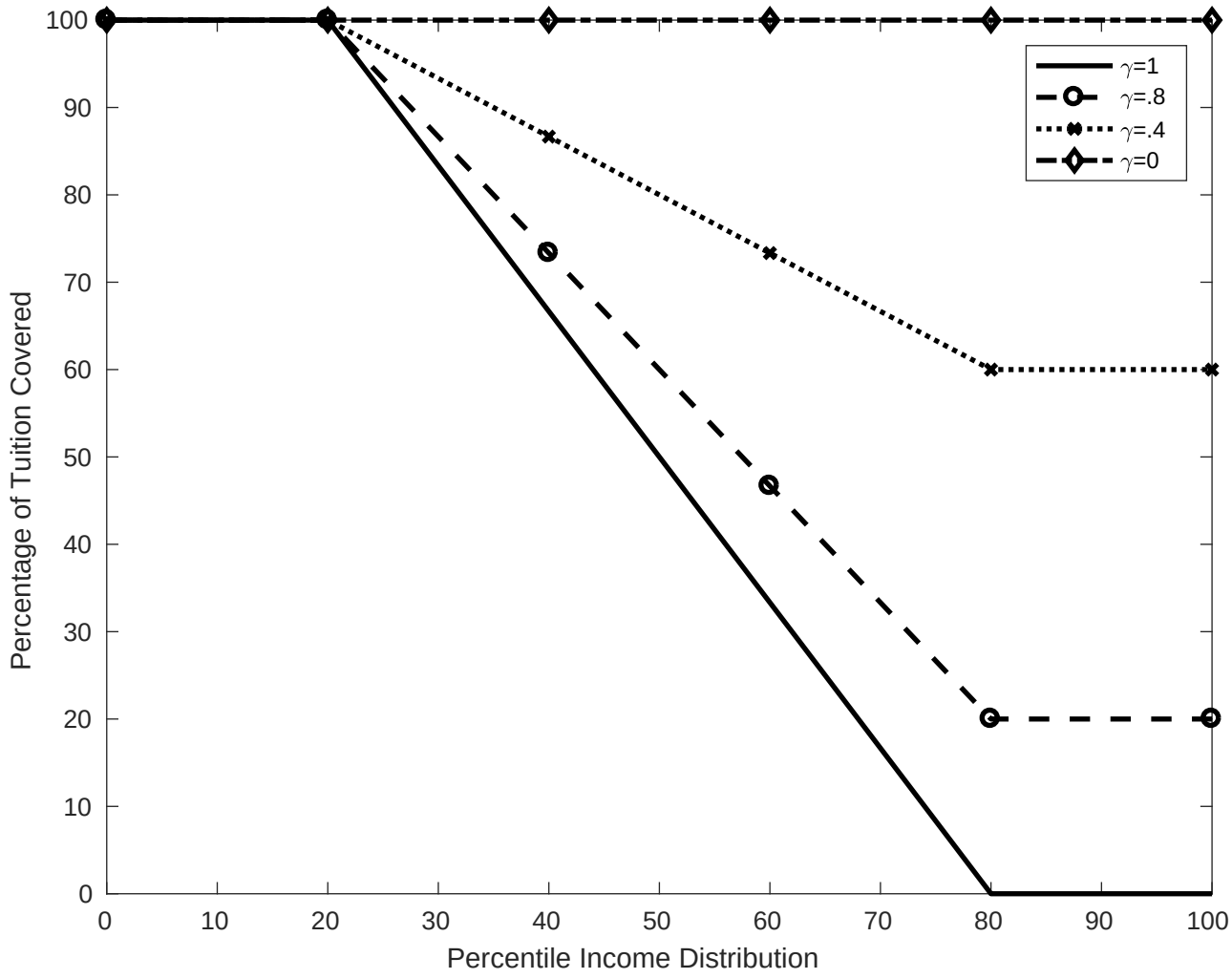
Notes: This figure shows the densities of average mathematics-language admission scores for students in the poorest 20% and wealthiest 20%. It also shows the change in the median admission cutoff using estimates of the common price model.

Figure 9: Enrollment Rate among Poorest 20% with Free Tuition and Differrent Capacity Expansion Levels



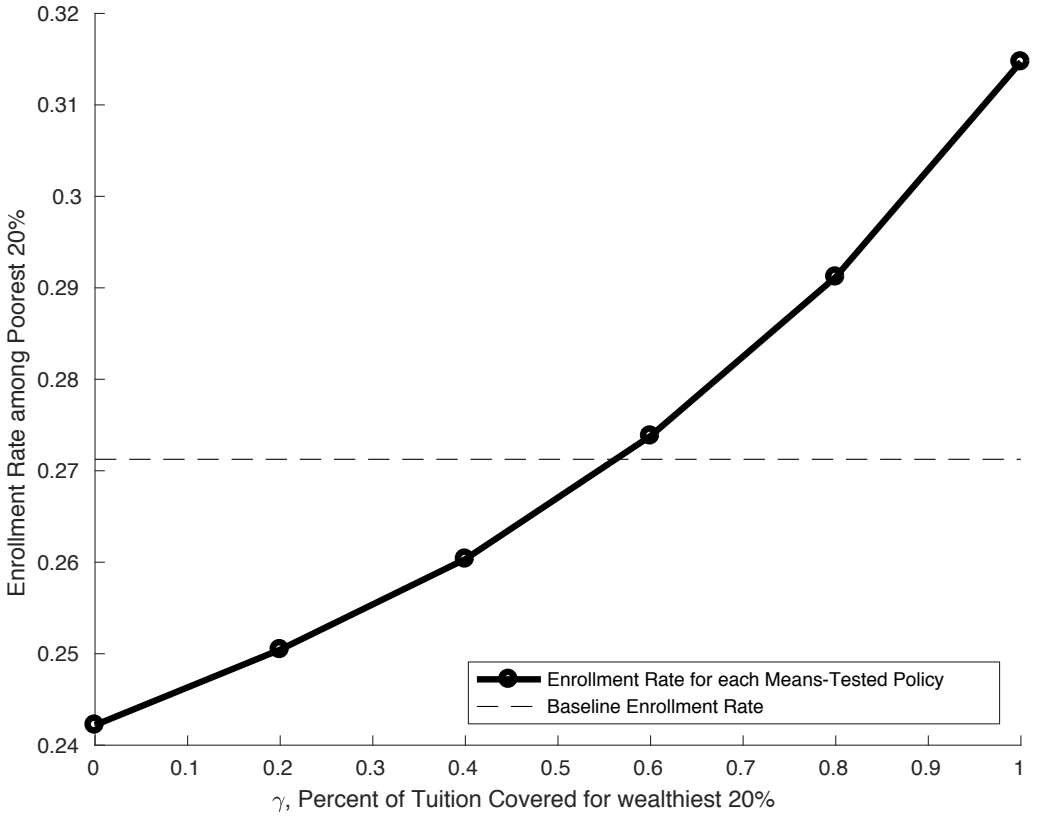
Notes: This figure shows the proportion of students in the poorest 20% enrolled under free tuition and different capacity expansions using estimates from the common price coefficient specification. The dashed line shows the baseline enrollment rate for this group. The solid line shows the enrollment rate after free tuition and the corresponding capacity expansion is introduced. For each counterfactual I construct a new simulated stable allocation.

Figure 10: Different Means-Tested Scholarship Schemes Evaluated in Counterfactuals



Notes: This figure presents different financial aid schemes commented in the main text. γ is the parameter that indexes how targeted financial aid is.

Figure 11: Enrollment Rate among Poorest 20% with Different Means-Tested Scholarships



Notes: This figure shows the proportion of students in the poorest 20% enrolled under different means tested policies indexed by the x-axis. See the previous figure 10 to see the exact means-testing counterfactual evaluated for each value of the x-axis. This figure uses estimates from the common price coefficient specification. The dashed line shows the baseline enrollment rate for this group. The solid line shows the enrollment rate for each policy. For each counterfactual I construct a new simulated stable allocation.

A Data and Institutional Details

A.1 Sources and Sample

All data was securely accessed at a computer in the Ministry of Education's building. A one year partially binned data set was shared for this project. The sources of information used in this project are:

- DEMRE
- SIES
- FUAS

All sources of information sent their data to SIES where the data was de-identified. I did not access any dataset with the real identifier number (RUT).

Table 14: Number of Scholarships per Income Quintile in 2015

	Quintile					
	20% Poorest	2nd	3rd	4th	20% Wealthiest	Total
Number of Students with Scholarship	13,029	20,706	17,802	7,359	0	58,896
Percentage of total scholarships	22%	35%	30%	12%	0%	-

Notes: Information based on the total number of new scholarships awarded for 4 to 5-year programs.

A.2 Centralized Admissions Algorithm

The student proposing deferred-acceptance algorithm, can be described as follows

Step 1) Each student proposes to her first choice. Each program tentatively assigns seats to its proposers one at a time, following their priority order based on the weighted score. Students are rejected if no seats are available at the time of consideration.

In general, in

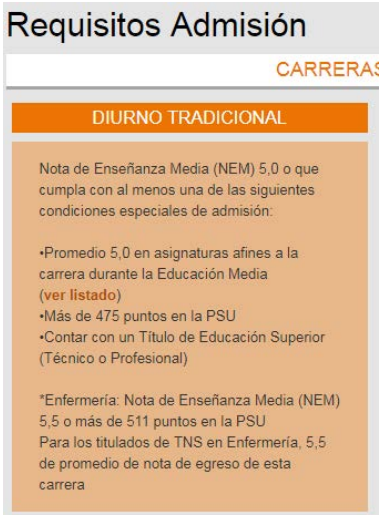
Step k) Each student who was rejected in the previous step proposes to her next best choice. Each school considers the students it has tentatively assigned together with its new proposers and tentatively assigns its seats to these students one at a time following the program's priority order. The student is rejected if no seats are available when she is considered.

The algorithm terminates either when there are no new proposals or when all rejected students have exhausted their rank order list of preferences.

A.3 Public Information on Admission Cutoffs

Figure 12: Examples of Public Information of Admission Cutoffs outside Centralized Admission System

(a) Universidad Iberoamericana



(b) Universidad de las Americas

Notes: Both exhibits show the minimum requirements for admission. In the first case, students need a GPA above 5 (scale from 1 to 7) or an average Math-Language admission score of 400, or have a vocational 2-year degree. In the second case, students need GPA above 5 or GPA above 5 in classes related to the major, or an average admission score above 475 or a vocational degree. Source: `http://www.uibero.cl/admision-2017/` and `http://admision.udla.cl/requisitos-admision`, both accessed 10/5/2017.

Figure 13: Examples of Public Information of Admission Cutoffs inside Centralized Admission System

Nombre	Puntajes de Corte 2017
Agronomía	554,70
Agronomía (Chillán)	527,20
Antropología	577,75
Arquitectura	600,95
Artes Visuales	574,00
Astronomía	617,15
Auditoría	539,45
Auditoría - Diurna (Los Ángeles)	500,60
Bachillerato en Humanidades	561,95
Bioingeniería	602,25

(a) Universidad de Concepcion

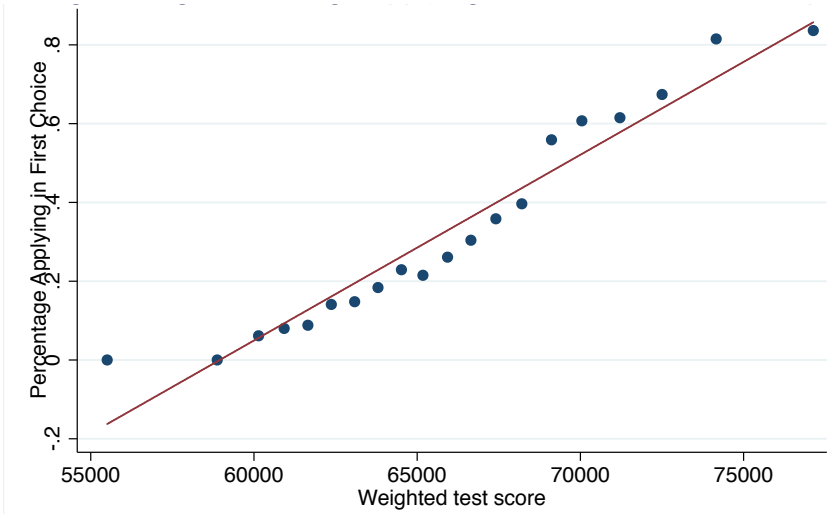
CARRERA	Selección	
	Máx.	Min.
27001-INGENIERIA CIVIL EN MINAS	785.8	500.3
27003-INGENIERIA CIVIL EN METALURGIA	668.7	500.9
27004-INGENIERIA CIVIL EN COMPUTACION E INFORMATICA	671.7	479.8
27005-INGENIERIA CIVIL INDUSTRIAL	723.5	512.3
27009-GEOLOGIA	750,0	535,0
27020-PSICOLOGIA	698.2	522.8
27021-LIC EN EDUC. Y PED. EN ED. FISICA	700.5	455.6

(b) Universidad de Atacama

Notes: Both exhibits show the minimum requirements for admission. In the first case, expressed as the weighted cutoff of last admitted in the previous year. Information corresponds to 2017 process, but every year universities in the centralized system publish a version of this in their websites.

A.4 Evidence of Manipulation of Rank Order Lists

Figure 14: Fraction Applying to a Selective University in First Choice



Notes: This figure shows, among students who rank first an Engineering program, the fraction that ranks University of Chile or Pontifical Catholic University first. The figures further restricts students to live in Santiago, where these both universities are located. The x-axis uses the weighted score used in admission process of University of Chile.

A.5 Maximum Ranking Requirements by Institution

As described in section 2.2, although the maximum number of options a student can rank when applying in the centralized admission system is 10, some institutions have a tighter limit. Table 15 presents the maximum number of applications that each institution will consider. This information is public and presented to students by institutions and by the formal communication of the centralized system published in the newspaper El Mercurio, and available online (DEMRE, 2015).

Table 15: Maximum Number of Options Considered in Ranking by University in Centralized Admission System

University	Maximum Place in Ranking to be Considered
Universidad de Chile	4
Pontificia Universidad Catolica de Chile	4
Universidad Arturo Prat	5
Universidad Austral	6
Universidad Andres Bello	6
Universidad Diego Portales	7
Universidad de La Serena	8
Universidad de Atacama	8
Universidad de Concepcion	10
Universidad Tecnica Federico Santa Maria	10
Universidad de valparaiso	10
Universidad Tecnica Metropolitana	10
Universidad de Tarapaca	10
Universidad de Antofagasta	10
Universidad de Playa Ancha	10
Universidad del Bio-Bio	10
Universidad de la Frontera	10
Universidad de los Lagos	10
Universidad de Magallanes	10
Universidad de Talca	10
Universidad Catolica del Maule	10
Universidad Catolica de la Santisima Concepcion	10
Universidad Catolica de Temuco	10
Universidad Mayor	10
Universidad Finis Terrae	10
Universidad Adolfo Ibanez	10
Universidad de los Andes	10
Universidad del Desarrollo	10
Universidad Alberto Hurtado	10
Mean	8.9
Median	10

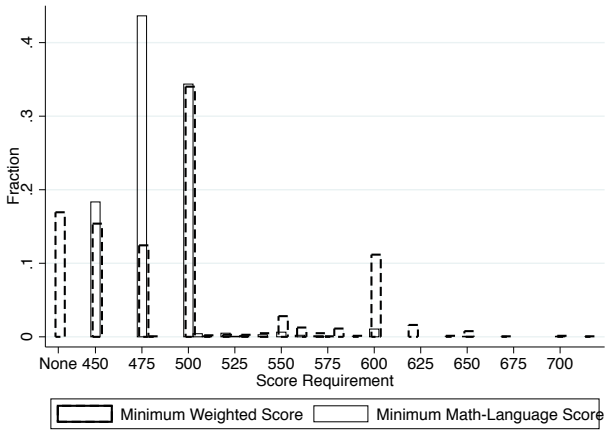
Notes: This information comes from the documents distributed by DEMRE (administering the centralized admission system), that are public to students and available online at `http://psu.demre.cl/publicaciones/`

A.6 Score Restrictions to Applications

All programs in the centralized admission system have a minimum requirement of the average mathematics and language score to apply. The solid bars in Figure 15 show the distribution with two important spikes, one at 475 points and a second one at 500 points. This second minimum requirement is used by a third of the programs and coincides with the eligibility cutoff for scholarship in 2015. Most programs also have a minimum weighted score, with 500 points being used by a third of the programs again. While this potentially creates a discontinuity in the set of programs a student is eligible for admission, it is an empirical matter whether these minimum restrictions bind at these programs, and what percentage of students bunch at this minimum requirements. I find that in practice, only 1.4% among all

programs has a binding minimum requirement at 500 points,[33] and among students enrolled in these programs only 0.06% of them have a binding minimum score of 500 points.[34] Figure 16 shows that the distribution of average mathematics and language scores is well above 500 points for almost all admitted students at these programs in fact. This means that while the minimum requirements are binding at some programs in the sense that it determines the minimum score, it does not bind for most students who decide to enroll at those programs.

Figure 15: Histogram of Score Requirements Among Programs in Centralized Admission System in 2015

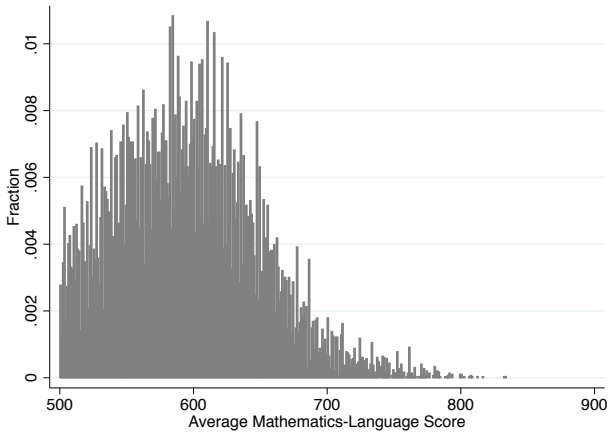


Notes: This information comes from the documents distributed by DEMRE (administering the centralized admission system), that are public to students and available online at `http://psu.demre.cl/publicaciones/`. In 2015 there are 1,422 unique programs.

[33]Defined as programs that require a minimum average mathematics-language score of 500 and that enroll at least one student with that minimum.

[34]In 2015 29,626 students enrolled at programs with a minimum requirement of 500 points of average mathematics-language.

Figure 16: Histogram of Scores Among Admitted Applicants at Programs with Minimum Requirement of 500 Points in Average Math-Language



Notes: This information comes from the documents distributed by DEMRE (administering the centralized admission system), that are public to students and available online at `http://psu.demre.cl/publicaciones/`. In 2015 there are 29,626 students admitted at programs with minimum requirement of 500 points in average Mathematics-Language.

B Regression Discontinuity Results

Table 16: Regression Discontinuity Effects on Enrollment for Extended Data Set and Multiple Bandwidth Selection Criteria

	Method of Bandwidth Selection			
	Robust	I&K	0.5 X I&K	2 X I&K
A. Enrollment at Institutions Eligible for Scholarship				
RD	0.0642***	0.0542***	0.0646***	0.0628***
	(0.0079)	(0.0050)	(0.0070)	(0.0036)
Mean	0.4650	0.5422***	0.5262***	0.5385***
		(0.0035)	(0.0050)	(0.0024)
N	101355	184326	95268	327830
Bandwidth	31.13	58.65	29.33	117.31
B. Enrollment at Any Institution				
RD	0.0402***	0.0389***	0.0426***	0.0354***
	(0.0053)	(0.0043)	(0.0060)	(0.0031)
Mean	0.7074	0.7493***	0.7405***	0.7494***
		(0.0031)	(0.0044)	(0.0022)
N	163800	183336	95268	327011
Bandwidth	51.69	58.34	29.17	116.68

Notes: This table uses data between 2011 and 2015 using the average Language-Mathematics score as running variable and conditioning on income eligibility, recentering the running variable by year and quintile using the corresponding eligibility criteria. Robust bandwidth uses the Cattaneo et al (2016) criteria implemented with rdrobust in Stata. I&K refers to the Imbens and Kalyanaraman (2012) bandwidth selection.

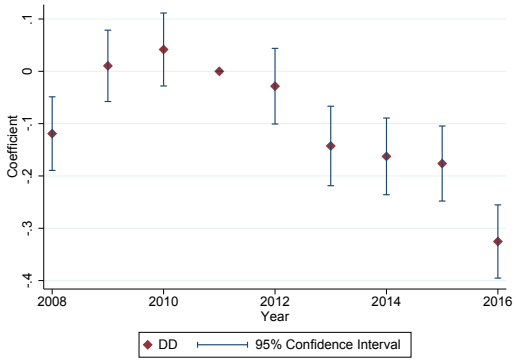
Table 17: Balance of Pre-determined Demographic Characteristics around the Eligibility Threshold

Demographic	Mean below Threshold	RD Effect
Mother Less than HS	0.361	0.0059
		(0.0052)
Father Less than HS	0.330	0.0148**
		(0.0059)
Female	0.560	0.0051
		(0.0058)
Mother Head of Household	0.370	-.0115**
		(0.0052)
Stay Home Mother	0.428	0.0013
		(0.0053)
Public HS	0.347	0.0067
		(0.0057)
Voucher HS	0.641	-.0064
		(0.0059)
Private HS	0.013	-.0003
		(0.0015)
GPA	5.734	0.0089
		(0.0065)
Number of Family Members	4.464	0.0370*
		(0.0196)

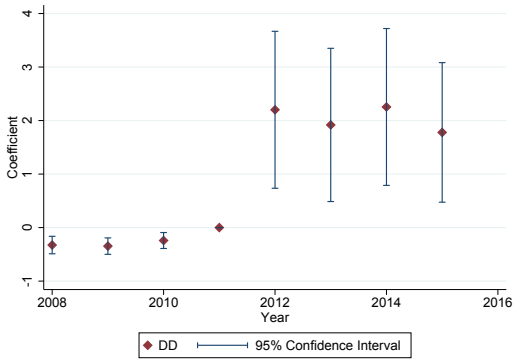
Notes: This table uses data between 2011 and 2015 using the average Language-Mathematics score as running variable and conditioning on income eligibility, recentering the running variable by year and quintile using the corresponding eligibility criteria. For each demographic variable I compute the optimal bandwidth using Imbens and Kalyanaraman (2012) bandwidth selection.

C Difference-in-Difference Results

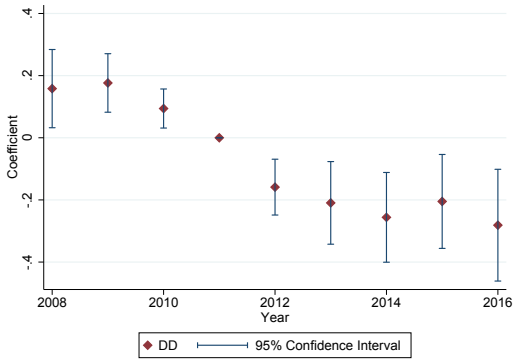
Figure 17: Evidence of Parallel Trends for Difference-in-Difference



(a) Change in share of students from poorest 40% with respect to 2011



(b) Change in cutoff for admission with respec to to 2011



(c) Change in enrollment with respect to 2011

D Details on Choice Set Construction

Students' choice sets contain:

1. One option for programs at CFT institution in the region of residence
2. One option for programs at Professional Institutes (IP is its spanish acronym) option in the region of residence
3. One option for 2-year programs outside of the student region of residence
4. One option for 4-year programs outside of the student region of residence
5. All 4-year or 5-year programs were the student clears the admission cutoff in the region of residence of the student

E Computational Details

E.1 Estimation Algorithm

I use the inner loop estimation procedure proposed in Berry (1994), in the version used in Berry et al (2004).

For a given value of θ I choose $\boldsymbol{\delta}(\theta)$ to match the market shares of the program aggregates detailed in 5.4. I find the value of $\boldsymbol{\delta}(\theta)$ that matches the market share using the procedure suggested by Berry (1994) in an inner loop. Then given, $(\theta, \delta(\theta))$ I compute the objective function given this and by inputting the analytical gradient I find the estimates using Knitro in Matlab.

E.2 Asymptotic Variance-Covariance

I compute the asymptotic variance for the Method of Simulated Moments. Let Δ be the derivative of the moments, $\Delta = \nabla_\theta g(\theta)$, then the asymptotic variance-covariance matrix is given by

$$V = (\Delta' W \Delta)^{-1} \Delta' W \Omega \Delta (\Delta' W \Delta)^{-1}, \tag{17}$$

where $\Omega = \Omega_a + \Omega_s$, with Ω_a corresponding to the variance-covariance of the moments if they were not simulated, and Ω_s is the additional variance introduced by the fact that the moments are simulated. $\Omega_a = \frac{1}{N}\sum_{i=1}^{N} g_i^s(\theta) g_i^s(\theta)'$ and $\Omega_s = \frac{1}{S}\sum_{s=1}^{S}(\sum_{i=1}^{N} g_i^s(\theta))(\sum_{i=1}^{N} g_i^s(\theta))'$.

F Estimation Results

This appendix describes some of the details on estimates omitted from the main text. Below I show the underlying parameter estimates that are and robustness to the aggregation of programs presented in 5.4.

F.1 Underlying Parameter Estimates

Table 18: Raw coefficients

Characteristics:			
Program	Student	Coefficient	SE
Price			
	Main Effect	-0.231***	(0.018)
Same Region			
	Main Effect	3.367***	(0.071)
Share of students from Public HS			
	Main Effect	-9.765***	(0.676)
	No HS Mother	-1.351***	(0.065)
	HS Mother	-1.213***	(0.057)
	Publich HS	1.708***	(0.142)
	Voucher HS	-2.035***	(0.144)
	Poorest 40%	0.655***	(0.074)
	Math-Language Average Score	-0.473*	(0.244)
Share of students from Poorest 40%			
	Main Effect	-7.915***	(0.592)
	No HS Mother	0.372***	(0.115)
	HS Mother	0.617***	(0.067)
	Publich HS	0.403**	(0.164)
	Voucher HS	1.145***	(0.187)
	Poorest 40%	-0.229***	(0.06)
	Math-Language Average Score	-15.07***	(4.365)
Average Math-Language Score of enrolled students			
	Main Effect	0.983***	(0.197)
	No HS Mother	-0.389***	(0.029)
	HS Mother	-0.329***	(0.017)
	Publich HS	0.38***	(0.029)
	Voucher HS	-0.448***	(0.031)
	Poorest 40%	-1.466***	(0.032)
	Math-Language Average Score	-1.726	(1.354)
Size			
	Main Effect	-32.734***	(5.228)
	No HS Mother	0.665	(0.535)
	HS Mother	1.924***	(0.315)
	Publich HS	-8.959***	(2.039)
	Voucher HS	8.353***	(1.834)
	Poorest 40%	24.104***	(0.905)
	Math-Language Average Score	11.669	(29.245)
STEM			
	Main Effect	-1.059***	(0.225)
	No HS Mother	0.008	(0.007)
	HS Mother	-0.03***	(0.007)
	Publich HS	-0.031	(0.049)
	Voucher HS	-0.033	(0.028)
	Poorest 40%	-0.744***	(0.043)
	Math-Language Average Score	3.211***	(0.606)

Notes: This table shows the raw coefficients from the common price coefficient model.

F.2 Robustness to Aggregation of Programs

In this subsection I will present robustness to the aggregation of unobserved characteristics described in 5.4.