Optimal Policy Design for Raising Teacher Quality

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Abstract

This papers studies the effects of higher education policies that aim to crowd-in and crowd-out students from pursuing certain degrees. My empirical application is of a policy launched in 2011 in Chile that aimed to raise teacher quality by crowding-in higher performing students into Education degrees, while crowding-out the lower-performing ones. Exploiting the sharp assignment rule, I estimate that, at the threshold, enrollment at teacher colleges increased by 30%, and there is a shift in the distribution of test scores. Students then proceed to perform better at the labor market, with students doing 0.1-0.15SD better in several measures of teacher quality. To understand the market structure and distributional consequences of the policy, as well as to perform counterfactual simulations, I develop a general equilibrium model of the higher education market within a centralized admission system. In doing so, I present a novel equilibrium notion for discrete-continuous games in sparse markets. Counterfactual simulations show that alternative policies could have outperformed the observed one in terms of student quality, but at the cost of either (i) a higher fiscal burden or (ii) reduced market share of teacher colleges.

Keywords: Education, financial aid, higher education, equilibrium effects.
JEL codes: H52, I22, I23, I25.

1 Introduction

In the higher education market, several policies targeted at both students and degrees coexist. They can be broadly categorized as crowd-in and crowd-out out policies. The first group are demand-led policies that induce students to self-select into degrees. The most common are monetary transfers including scholarships, grants or subsidized loans, and can take varying forms depending on their objective. Two examples are income-based scholarships, targeted at reducing the educational gap between rich and poor, and merit-based scholarships that incentivize effort before and during higher education studies. Other examples of crowd-in policies are mentoring, research possibilities or networking. This policies can be general, if they're just targeted at higher education enrollment, or specific, as is the case for scholarships targeted at STEM degrees. Crowd-out policies restrict students from pursuing certain degrees. A typical case are minimum competency standards where students have to score above a given threshold in a college entrance exam. Many countries have different high school tracks, and the type of higher education a student can enroll depends on the type of high school he graduated from. While many policies are mandatory, others may be optional, and colleges choose to participate depending on the setting. An example of a voluntary policy is a scheme where the government subsidizes schools when enrolling students from specific backgrounds. While crowd-in and crowd-out policies can be independently implemented, it's likely that they interact in the achievement of certain target.

This paper studies the equilibrium effects of targeted policies in higher education, that is, policies that crowd-in and crowd-out students from pursuing certain degrees. I consider two instruments that the government can set: (i) an eligibility rule for funding (scholarships, grants or others) and (ii) a rule that restricts students from enrolling in certain degrees. Also, the government decides whether the program is optional or mandatory for colleges. Multiple policies can coexist in the market. Upon implementation, the observed equilibrium will be the result of this two-component policies, and each component comprises its own dynamics. First, the monetary incentive will tend to crowd-in targeted students who, in absence of the policy, would have enrolled in a non-targeted degree. The crowd-out rule has (i) a direct, mechanic effect of crowding-out every student who does not fulfill it and (ii) an indirect effect given by the change in peer composition, which makes those degrees more or less attractive to other students. The magnitude of this effect will depend on the extent to which students value peer composition. From the supply-side, colleges are expected to be affected and react differently to this type of policies depending on things such as their quality and market power. To better understand the mechanisms that drive the observed equilibrium, I build a model of the higher education market within a centralized admission system, where the government sets the rules of the policy, colleges make a joint discrete-continuous choice of participation and tuition setting, and students choose among available college-degree pairs while trading off different features such as quality, peer composition, distance and fees. I present a novel equilibrium concept for markets that are sparse and with a high number of players. In this equilibrium, players respond only to the decisions of their close rivals. This notion not only makes it computationally feasible to solve this type of games, but also better captures the heuristic performed by decision makers. I present a rule for determining how "close" a rival is, as well as how many rivals' decisions should be considered in equilibrium.

My empirical application is of a program launched in 2011 by the Chilean Ministry of Education, named *Beca Vocación de Profesor* (BVP), which seek to attract high performing students to become teachers. The program includes a scholarship that fully covers tuition and fees. Students whose admission score is sufficiently high receive an additional stipend. As a counterpart, scholarship holders must (upon graduation) teach in a publicly funded school for a fixed number of years. As it represents a significant transfer to students (the yearly tuition equals 6-10 minimum wages) virtually every eligible candidate who enrolls in an Education degree takes the scholarship. Importantly, the program also imposes a performance floor to universities but participation is optional. For the most elite colleges, the cutoff score for enrolling in teaching degrees was above the imposed floor, so participation was strictly preferred. The lower quality colleges, however, offered degrees where most of the cohort scored below this floor, so it wasn't profitable to participate and opted out. In the margin, there might have existed some degrees where the gains from participating exactly offset the loses. Given this heterogeneity, the optimal policy is ex-ante not obvious. A sufficiently high performance floor would make most universities opt out, reducing the overall impact of the program. If, on the contrary, the performance floor was very low, for most degrees this component of the policy would have been not binding. A low eligibility cutoff would make the program costlier and the average quality of students lower, while a very high eligibility cutoff might have attracted very few high performing students.

When evaluating the impact the program had on enrollment, we face the fundamental problem of inference: for each individual, we don't know his counterfactual enrollment in the absence of the policy. Even if we observe a year-to-year increase in teaching enrollment, it could very well be for reasons unrelated to the program, which would therefore only consist in a lump-sum transfer to teaching students. However, the rules of the program provide a clean identification strategy. First, I show that the program was successful in attracting higher performing students to the teaching career. I exploit the characteristics of the eligibility rule, which allows to perform a regression discontinuity (RD) design. I estimate that students who scored just above the cutoff (top 20% of the exam distribution) have a 30% higher probability of enrolling in a teaching degree. This effect is robust to alternative model specifications, covariate selection and bandwidth. Second, by means of a Differences-in-Difference (DID) analysis, I find that the policy also had an effect on the labor market, that is, this increase in student quality translated into better teachers, with a 0.112SD effect in Teacher Value Added (TVA) and 0.119SD increase in a Teacher Evaluation program by the Ministry of Education on public school teachers.

The policy sets in motion several forces that determine the observed equilibrium. The inflow of higher performing students make available slots on top colleges more scarce. Students who score below the new cutoff can choose to enroll in a lower quality teaching degree or switch to a non-teaching degree (besides from not enrolling at all). Lower quality degrees then face an influx of students from top colleges, while their cohort also improves because of the performance floor. This double effect might also attract students from other areas who now find these degrees more appealing. From the supply side, universities can react to this increase in demand for teaching degrees by adjusting tuition or opening new degrees, which will also impact enrolling decisions. I simulate counterfactual settings of the two-folded policy. Results show that alternative policy rules succeeds in raising the quality of students that pursue Education studies. However, the policy faces two trade-offs: the increase in quality comes at the cost of: (i) a higher fiscal burden, as the number of scholarship holder increases, (ii) lower market shares, as students are crowded-out of education programs, or (iii) both effects simultaneously.

This paper builds upon several strands of literature. It contributes to the research on higher education financing. Multiple articles show the effectiveness of policies that partially or fully cover tuition on enrollment (Angrist et al., 2014, Denning, 2017, Londoño-Vélez et al., 2020, Dobbin et al., 2022) and graduation (Dynarski, 2003, Cohodes and Goodman, 2014, Denning, 2018). Also, it has been shown that they type of financial instrument impacts major choice (Arcidiacono, 2005, Rothstein and Rouse, 2011). In the special context of Chile, Solis (2017) studies the impact of credit access on college enrollment, finding that subsidized loans double the enrollment rate for eligible candidates. Part of my analysis builds on his empirical strategy, based on test score discontinuities for eligibility. However, my focus is not on loans but on instruments that impose no repayment, such as grants or scholarships, and I complement with a structural model to quantify the contribution of each component of the composite policy.

This paper also contributes to a series of papers that estimate the effect of education policies through the lens of structural models. Neilson (2021) builds a model of supply and demand for primary education and study the competitive effects of voucher policy, finding that it made schools improve their quality due to an increase in competition. Dinerstein and Smith (2021) develops a model of supply and demand of private schooling to study the effect of a public school funding reform in Chile. They find that it increased exit and it decreased entry for private schools. In the higher education sector, Dobbin et al. (2022) build a supply and demand model to study the effect of subsidized student loans on prices and enrollment, and Otero et al. (2021) study the distributional consequences of affirmative action (given by quotas) within a centralized assignment system. This article studies the equilibrium impacts of targeted policies, both on the market structure and on student outcomes.

The remainder of this paper is as follows. Section 2 explains the conceptual framework for targeted policies. Section 3 gives details of the policy under analysis and the higher education market in Chile. Section 4 gives descriptive evidence of the policy impact. Section 5 presents the equilibrium model of the higher education market. Section 6 show the estimation results. Section 7 concludes.

2 Conceptual Framework

There exists a set $\mathcal{I}$ of individuals such that $i \in \mathcal{I} = \{1, ..., n\}$, and a set $\mathcal{J}$ of college degree programs such that $j \in \mathcal{J} = \{1, ..., J\}$. In each period $t \in T$, the government announces K policies that can be summarized by $P = (\mathcal{E}, \mathcal{F}, M)$, where $\mathcal{E}$ and $\mathcal{F}$ are sets with J elements, and M is a $J \times K$ matrix. The set $\mathcal{E}$ is composed of functions that determine the type of funding a student will receive from the government if enrolled at each degree[1], based on characteristics x_i that are observed by the policy maker. The funding rule can be summarized by λ_{ij} and T_{ij}, where the former is the percentage of tuition coverage and the latter is a direct transfer from the government to the student. The set $\mathcal{F}$ is composed of functions that determine if a student is allowed to enroll in each degree, taking value 1 if allowed and 0 if not allowed. Given P, it's possible to construct the vectors E and F of dimension $I \times J$ with typical elements e_{ij} and f_{ij} that indicate, respectively, the funding and admissibility of student i in degree j. The absence of any policy implies $e_{ij} = (0, 0)$ and $f_{ij} = 1$. Finally, $m_{jk} = \{0, 1\}$ takes value 0 if the rules for policy k are optional and 1 if they are mandatory.

[1]Note that the functions can be the result of multiple overlapping policies.

Let's consider two simple cases. In the first, the government launches a unique policy for degree j, involving a scholarship that covers a percentage λ of tuition and transfers a monetary amount T to every student who has an income Y_i below τ. Participation is optional. In this case, we have

$$\begin{aligned} e_{ij} &= \begin{cases} (\lambda, T) & \text{if } Y_i < \tau \\ (0,0) & \text{if } Y_i \geq \tau \end{cases} \text{ and participates} \\ &= (0,0) \text{ if doesn't participate} \end{aligned}$$

and $e_{ik} = (0,0)\ \forall k \neq j, i \in \mathcal{I}$. Also, $f_{ij} = 1\ \forall j \in \mathcal{J}, i \in \mathcal{I}$, $m_j = 0$ and it can trivially take value 0 or 1 for the other degrees.

A second example is the case where the government imposes a score $S_i > q$ for students who wish to enroll in any higher education degree. The rule is mandatory for everyone. In this case, we have, $\forall j \in \mathcal{J}$:

$$\begin{aligned} f_{ij} &= \begin{cases} 1 & \text{if } S_i > q \\ 0 & \text{if } S_i \leq q \end{cases} \\ e_{ij} &= (0,0) \\ m_j &= 1 \end{aligned}$$

This framework can easily be generalized to more complex scenarios that can be incorporated in $\mathcal{E}$ and $\mathcal{F}$, such as multiple scholarships and grants with different objectives that coexist. It does not accommodate other types of policies, such as those where quotas are imposed, or when colleges are subsidized if they enroll students from certain backgrounds.

3 Background

In this section I provide a description of my empirical application. Section 3.1 describes the market structure for the Chilean higher education system, section 3.2 describes the policy and provides some evidence of its effects, and section 3.3 describes the data sources and includes descriptive statistics on the estimating sample.

3.1 Higher Education Market

The higher education market in Chile is composed of 156 institutions, from which 60 are Universities and the rest are Tertiary institutions who offer Short Cycle Programs. Within the universities, some are part of the centralized admission system, named *Sistema Unico de Admisión* (SUA), and the rest perform their admission process outside the system. In the time frame of my study, 25 universities participated initially on the centralized system, while in 2012 it was expanded from 25 to 33. Students who wish to apply through the centralized admission system must take the *Prueba de Selección Universitaria* (PSU), a national standardized test for higher education admission. Two parts are mandatory (Mathematics and Language) while two are optional (Social and Natural Sciences). Once students have their test results, they proceed to submit a list with at most ten college-degree pairs (which I will refer to as programs), by order of preference. When applying, they have information on each program's vacancies and requirements, such as a minimum application score. Finally, given vacancies and the ordered lists of both sides of the market, the centralized assignment mechanism matches students to programs. Every degree inside the platform is required to apply a cutoff of at least 450 points. Simultaneously, students can apply and enroll in off-platform programs, which are generally of lower quality and where universities can freely impose a PSU requirement on a degree-by-degree basis.

In the period under study, the main existent scholarships were *Beca Bicentenario* and *Beca Juan Gómez Millas*, which covered approximately 80% of tuition for students in the first two quintiles of the income distribution, who scored above 550 points in the PSU (an average of the Mathematics and Language component)[2]. The other most common instrument to finance higher education were college loans, notably a government-subsidized scheme called *Crédito con Aval del Estado*, which required a PSU average above 475 points, excluded students in the richest quintile and financed up to full tuition in any accredited higher education institution.

[2]The former only included degrees in traditional universities (called CRUCH), while the latter included any degree at an accredited institution

3.2 Teacher College Scholarship

Education is the most popular degree of the Chilean higher education system (Kapor et al., 2022), therefore the shortage of teachers is not a concern. However, the performance of students who enroll in Education degrees is substantially below those of other fields. With the goal of attracting distinguished students to the teaching career, the Chilean Ministry of Education (MINEDUC) launched in 2011 *Beca Vocación de Profesor* (BVP), a policy that subsidizes all tuition and fees at participating teaching degrees. Since its launching, BVP has two type of beneficiaries:

- High school graduates who wish to enroll at teacher colleges.
- Holders of a Bachelors degree (or in their last year of studies) who want to take a pedagogical complement (2 years long) to become teachers.

My analysis will be on the first subset of beneficiaries. Eligible candidates must have scored an average above 600 points in the Language and Mathematics components of the PSU (which corresponds to the top 20% of scorers). Alternatively, students could qualify to the scholarship if they finish school in the highest 5% GPA of their cohort and score an average above 580 points (in practice, less than 2% of scholarship holders qualified through this channel). The program also establishes a second, higher threshold of 700 points (approximately the top 5%) and students who score above it get, besides all tuition and fees covered, a monthly stipend and funding for doing an exchange abroad. The BVP was designed with the goal of attracting better students to the teaching career (as measured with outcomes prior to their higher education) and it doesn't impose a socioeconomic requirement, that is, even students from rich backgrounds are eligible. Technical reports show that, after implementation, a higher share of above-average test-takers enrolled in teaching degrees[3].

A condition for receiving the scholarship is that, upon graduation, beneficiaries have to work on a public-financed educational establishment for a 3 years. The spirit of the scholarship is not only to raise overall teacher quality but also to attract better teachers to schools where lower-SES students attend, in search of shrinking the achievement gap.

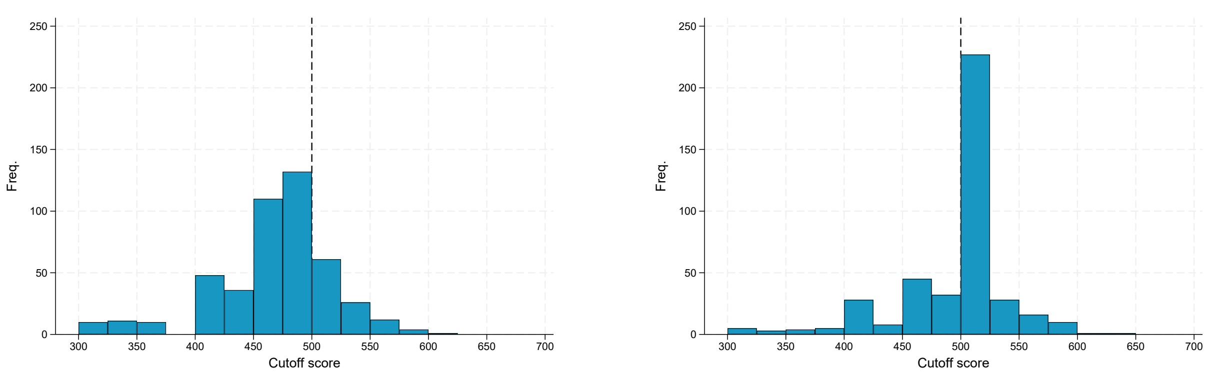
The policy also imposed a condition for participating teacher colleges. If they wanted their students to benefit from the BVP, they had to implement a floor on PSU scores at the national mean (500 points). For the most elite universities, this requirement was not binding as the cutoff score for teaching degrees is above this floor. However, for many universities this

[3] See, for example, Bonomelli, 2017.

requirement implied a sizable reduction in enrollment, so they decided to opt out of the program. Figure A1 shows the distribution of test scores for different groups of teacher colleges. While for the top teacher colleges the floor would not impact their enrollment (their cutoffs are already above this floor), those colleges with the lowest scoring students have virtually all of their enrollment below the 500 floor. For the Median college, it's not straightforward to assume which decision will lead to higher revenues. Figures 1a and 1b show the distribution of cutoff scores in teaching degrees in 2010 and 2011, respectively. First note that every degree who applies a cutoff score below 450 points correspond to an out-of-platform degree. In 2010, most of the degrees locate within the 450-500 points segment, but in 2011 there is a shift towards the 500-550 segment, which shows the high adherence of colleges to the policy. However, still there is a considerable part of the distribution below the 500 points cutoff, of degrees that opted out. Figures 2a and 2b show the distribution of test scores at participating and non-participating teaching degrees, respectively. For participating degrees, we can observe two changes between 2010 and 2011: the first is on the left tail, due to the performance floor imposed by the policy. The second one is on the right tail, where there is a higher density of students who scored above 600 points. As it's the eligibility score for the scholarship, it constitutes evidence in favor of the conjecture that the policy attracted higher performing students to teaching degrees. For degrees that opted out, however, the distribution of test scores between 2010 and 2011 is virtually the same, which indicates that the effect of the policy is concentrated in participating degrees, and non-participating degrees appear to have no spillovers effects.

Figure 1: Cutoff score at teaching degrees

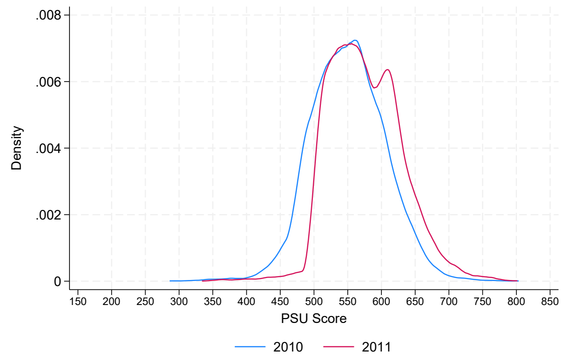
(a) 2010 **(b)** 2011



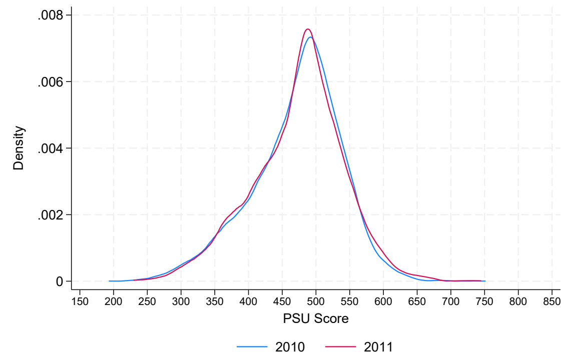
Notes: These figures show the histograms for enrollment at teaching degrees in (a) 2010 and (b) 2011. These figures include both inside and out-of platform teaching degrees.

Figure 2: Test score distribution at teaching programs

(a) Participating



(b) Non-Participating



NOTES: These figures show the distribution of test scores in 2010 and 2011 for (a) Participating and (b) Non-Participating teaching degrees. These figures include both inside and out-of platform teaching degrees.

3.3 Data

I compile information from multiple sources. Administrative records on the universe of high school and college students, scholarship application and scholarship assignment was provided by the chilean Ministry of Education (MINEDUC). The Department for Educational Evaluation, Measurement and Registry (DEMRE), a technical organisms of the University of Chile provided data on PSU results, as well as demographic information of test takers. Finally, the National Council of Education (CNED) provided information on higher education institutions, including tuition, vacancies and admission cutoffs. My sample consist on every student who took the university entrance exam for the years 2010 to 2012.

Tables 1 and 2 show descriptive statistics for degrees and test takers, respectively. From every bachelor-granting institution, close to a half operate within the centralized admission system, arguably the most selective and the higher quality universities. From all test takers, around 60% enroll in a higher education institution, and 20-30% do so within the centralized admission mechanism. In 2012 the number of institutions inside the centralized admission system grew from 25 to 33, which resulted in a 50% increase in the listed degrees and in-platform enrollment. The new institutions were less selective but more expensive, which is reflected in the change in average tuition and cutoff scores. Also students from higher socioeconomic status took the college entrance exam, as seen in the demographic variables (family income, mother's education and the type of school attended). Out-of-platform degrees are more heterogeneous, but overall less selective. The more prestigious (and also expensive) entered the system in the 2012 expansion. Around 15% of students who enroll do so in an

Education degree, making the policy relevant enough for considering equilibrium effects. In the periods after the policy was implemented, enrollment in Education degrees fell, which could suggest that more students were crowded out than the ones crowded in

Table 1: Descriptive statistics, degrees

	2010	2011	2012
All			
Colleges	63	63	65
Degrees	2855	3004	3023
Santiago	.323	.326	.330
Tuition	4206	4216	4326
Full Capacity	.399	.359	.326
Has Cutoff	.711	.621	.727
Cutoff Score	493	502	491
Inside Platform			
Colleges	25	25	33
Degrees	1014	1020	1407
Santiago	.236	.231	.322
Tuition	4178	4255	4736
Full Capacity	.585	.527	.464
Has Cutoff	1	1	1
Cutoff Score	527	526	516
Outside Platform			
Colleges	38	38	32
Degrees	1841	1984	1616
Santiago	.372	.375	.337
Tuition	4222	4196	3936
Full Capacity	.296	.273	.205
Has Cutoff	.552	.427	.489
Cutoff Score	465	479	453

NOTES: This table shows descriptive statistics on every bachelor degree from an accredited institution. The dummy variable *Santiago* takes value 1 if the degree is imparted in Chile's capital city. Tuition is expressed in constant US dollars from 2009.

Table 2: Descriptive statistics, students

	2010	2011	2012
Enrollment			
N Students	251634	250758	239367
Enrolled in platform	.204	.202	.298
Enrolled out of platform	.405	.425	.346
Not enrolled	.390	.372	.354
Demograhics			
Family Income	3.2	3.3	3.5
Private School	.100	.101	.111
Private Health	.268	.264	.275
Father With College	.162	.164	.175
Mother Employed	.387	.403	.416
Field			
Business	.126	.128	.126
Farming	.025	.024	.023
Art and Architecture	.056	.052	.050
Basic Sciences	.031	.030	.032
Social Sciences	.089	.088	.088
Law	.040	.038	.037
Education	.145	.141	.132
Humanities	.011	.011	.011
Health	.209	.218	.228
Technology	.257	.261	.261

Notes: This table shows descriptive statistics on every student who enrolled and took the college entrance exam. Family income is categorized in 1-10 brackets, and field clasification is performed following the ISCED-UNESCO guidelines.

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4 Policy effects

This sections presents empirical evidence of the policy effects. Section 4.1 assess if the program succeeded in attracting good students to become teachers by performing a regression discontinuity (RD) analysis. Section 4.2 shows the labor market effects of the policy, that is, if better students do actually manage to perform better as teachers, following a Differences-in-difference (DID) analysis.

4.1 Enrollment effects

I exploit the discontinuity in program eligibility around the 600 points cutoff, and thus I compare students who scored just below and just above this cutoff. My estimation strategy closely follows Solis (2017), and estimation is performed for the 2011 sample, the year in which the program was implemented.

I estimate the following equation:

$$EnrolledTeaching_i = \alpha_0 + \alpha_1 \cdot \mathbb{1}(s_i \geq e) + f(s_i - e) + \alpha_2 X_i + \epsilon_i \tag{1}$$

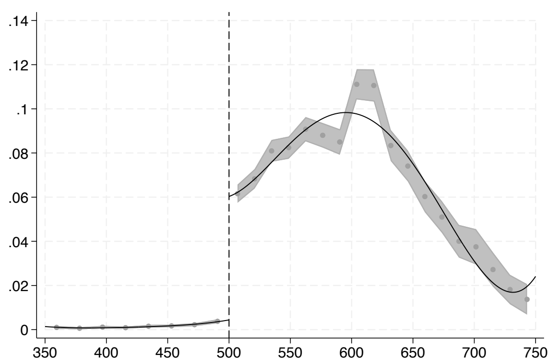
where $EnrolledTeaching_i$ is a dummy variable that takes value 1 if student i enrolled in a teaching degree, the indicator function $\mathbb{1}(s_i \geq e)$ takes value 1 if student's i test score s_i is above the cutoff value e, $f(s_i - e)$ is a function that controls flexibly for the impact of the test score on the outcome, and X_i are individual-level covariates. The parameter of interest is α_1, the effect of program eligibility on teacher degree enrollment. Since take-up is not perfect (although very high), the estimate is interpreted as an intention-to-treat effect.

In Figure 3, I plot the mean enrollment at teacher colleges within bins of PSU scores, with a 4th degree polynomial fit on different sides of the thresholds. Figures 3a and 3b are the plots for participant and non-participant teaching degrees, respectively, where the fits differ on each side of the 500 points threshold, while figures 3c and 3d do the same for the 600 points threshold. We can see that for people that scored below 500, mean enrollment is zero, showing the correct implementation of the policy. At the 600 points threshold, there is a discontinuous jump in teacher enrollment, something that points out to the effectiveness of the policy in attracting higher scoring students. For non-participant degrees, mean enrollment is increasing in test scores until 500 points, the floor imposed to participating degrees. At that threshold, not only mean enrollment starts to decrease, but also there exists a discontinuous jump in mean enrollment. I interpret this as students switching away from non-participant degrees to those that participate in the program. Even though students in this score segment don't qualify for the scholarship, they get to enter higher quality degrees. There also exists considerable enrollment for people that scored above the cutoff, which suggests that students might trade off other attributes besides from quality (such as price or geographic location) when considering enrollment. Finally, there are no discontinuities at the 600 points, something expected given that scoring above that threshold give no benefit at non-participating degrees.

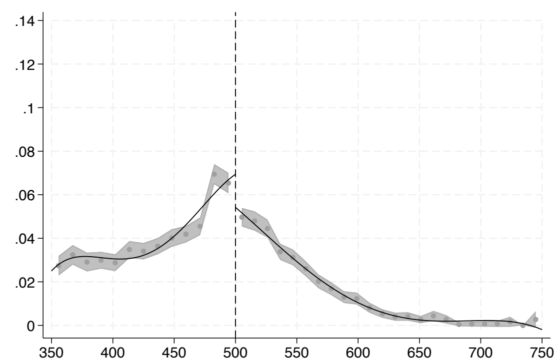
Table 3 shows the results of estimating equation 1 on the different thresholds, by fitting a local linear regression on each side of the threshold. At the 500 points cutoff, enrollment at participant teacher colleges increases from 0 to 5.2%. At the 600 points cutoff, there is an effect of 3.7 percentages points in enrollment. Considering that mean enrollment below the cutoff is 9.7%, it represents a 28% increase in the probability of enrolling at a teacher college. At the 700 points threshold the effect is of 2.5 percentage points. Considering that below the threshold those students where already benefiting from full tuition covering, the increase is associated to the additional stipend. Even though much less observations are used within the optimal bandwidth, estimation is still significant at the 1% significance level.

Figure 3: Enrollment at teacher colleges

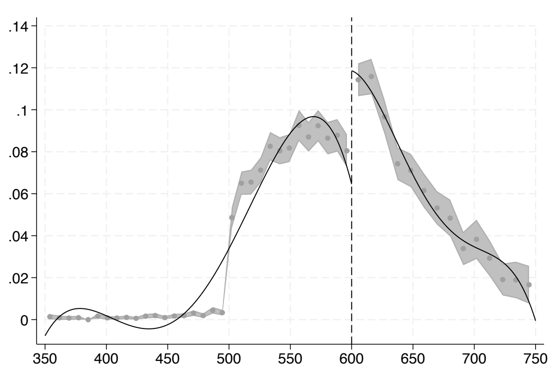
(a) Participant degrees, 500 points cutoff



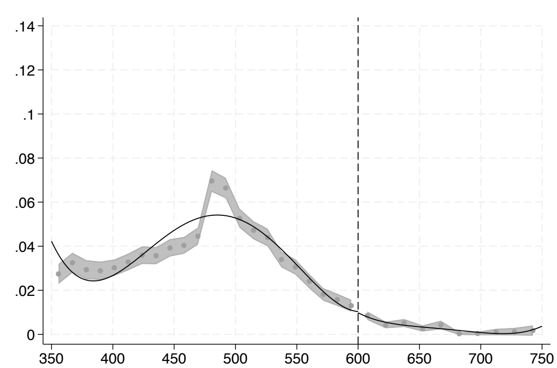
(b) Non-participant degrees, 500 points cutoff



(c) Participant degrees, 600 points cutoff



(d) Non-participant degrees, 600 points cutoff



NOTES: These figures plot mean teacher enrollment at participant and non-participant teaching degrees, with bins constructed via an IMSE-optimal evenly-spaced method using spacings estimators, following Calonico et al., 2015. In 3a and 3b, a 4th degree polynomial is fit on each side of the 500 points cutoff, while in 3c and 3d the same is done for the 600 points cutoff. Every plot is obtained using the 2011 data.

A number of confounding issues may arise with this strategy. First, I will check the correct implementation of the program by testing if scoring above the cutoff implies a change

Table 3: RD estimates of teacher enrollment

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05232***	0.03657***	0.02437***	-0.01779***	-0.00288	0.00121
	(0.00269)	(0.00633)	(0.00901)	(0.00306)	(0.00224)	(0.00075)
Cutoff	500	600	700	500	600	700
Observations	78258	42674	8752	105408	42674	16213
Bandwidth	44.1	36.3	26.5	61.4	36.1	45.7
Mean	.004	.086	.039	.067	.014	.000

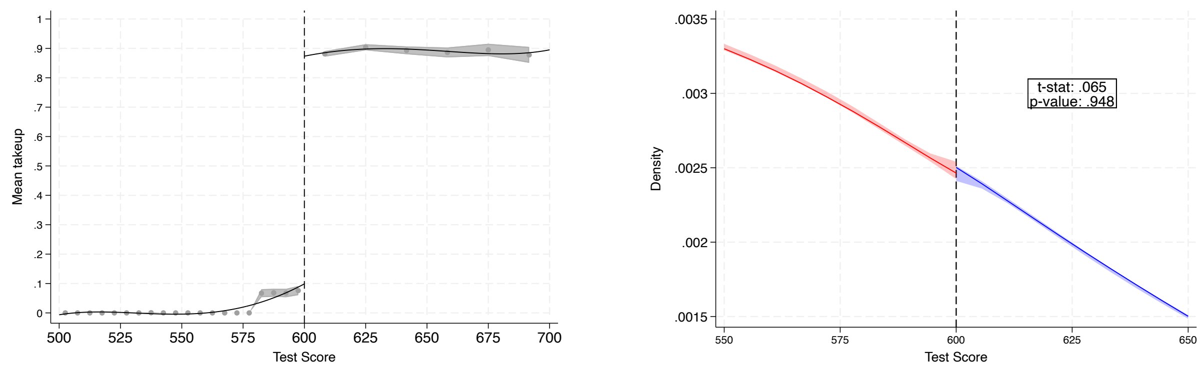
NOTES: This table shows the estimates from the RD design. Estimation is based on the sample of full test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing MSE.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

in takeup probability. Second, a discrete jump in scores around the cutoff could imply score manipulation or that students differ in unobserved ways that could explain enrollment at teacher colleges. That could happen because the 600 point threshold is specific to this scholarship, and students may seek to score just above in order to receive the scholarship. Third, eligible candidates could be systematically different in their observable characteristics.

Figure 4a shows the mean program take-up depending on test scores. First, note that take-up slightly increases below 600 points. That is for the few holders who qualified by finishing high school in the top 5% GPA of their cohort and scoring above 580 points (less than 2% of all scholarship holders). Take-up is zero before the 580 points requirement, and then discontinuously increases after the 600 points cutoff. Also, note that mean takeup after the cutoff almost exactly coincides with mean enrollment at teaching degrees, which shows that program take-up among eligible candidates was almost perfect, even though the scholarship imposes holders the requirement of teaching at publicly-funded schools for three years upon graduation. The program, therefore, might have discouraged students of enrolling in a teaching degree but, conditional on enrollment, it didn't dissuade them of taking the scholarship. Figure 4b shows no discontinuity around the cutoff, evidencing that students couldn't influence their final score (besides from exerting effort). Table 4 shows the result of estimating Equation 1 on observable characteristics. The first two columns use the full sample, columns 3 and 4 show the results for every student that enrolled in higher education, and columns 5 and 6 the results for every student who enrolled in a teaching degree. Results show that there are no mostly no discontinuities in observable characteristics between students just below and above the 600 points threshold, within the selected bandwidth. For students which score just above the cutoff the probability that a student's parent has a college degree is 2% lower, which indicates that students with better educated parents tend to choose different fields than Education.

Figure 4: Robustness checks

(a) BVP Takeup **(b)** PSU density



NOTES: Subfigure (a) plots mean BVP takeup among all test takers within bins of PSU scores, with a quadratic fit on each side of the 600 points threshold. Subfigure (b) shows the kernel density estimation of PSU scores. Both figures are obtained using the 2011 data.

Table 4: RD estimates on observable characteristics

	All		Enrolled		Teaching students	
	(1)	(2)	(3)	(4)	(5)	(6)
	Estimate	SE	Estimate	SE	Estimate	SE
Female	0.00447	(0.00972)	0.00970	(0.0108)	–0.0623**	(0.0274)
High School GPA	–0.695	(1.56)	–0.525	(1.66)	–7.70	(4.73)
Public HS	0.00199	(0.00693)	0.000184	(0.00750)	–0.00355	(0.0285)
Voucher HS	0.00580	(0.00861)	0.00442	(0.00907)	0.00514	(0.0249)
Private HS	–0.00854	(0.00719)	–0.00825	(0.00780)	–0.00752	(0.0177)
Santiago	0.00868	(0.00880)	0.0209**	(0.0104)	0.0417	(0.0280)
Family Income	–0.0363	(0.0505)	–0.109*	(0.0585)	–0.197	(0.140)
Private Health	–0.0168*	(0.00882)	–0.0158*	(0.00949)	–0.0407	(0.0278)
Father With College	–0.0234***	(0.00839)	–0.0181**	(0.00903)	–0.0393*	(0.0226)
Mother With College	–0.0225***	(0.00741)	–0.0277***	(0.00839)	–0.0355	(0.0226)
Father Employed	–0.00663	(0.00699)	–0.00527	(0.00729)	0.00689	(0.0285)
Mother Employed	–0.0189**	(0.00935)	–0.0184*	(0.0103)	–0.0371	(0.0316)
N	250,758		157,432		17,406	

Notes: This table shows the result for the RD estimation on observable characteristics around the 600 points cutoff. The first two columns show the regression discontinuity results for all test takers, columns 3 and 4 for every enrolled student, and columns 5 and 6 for students enrolled in teaching degrees. Bandwith selection is obtained for each characteristic independently. The dummy variable *Santiago* takes value 1 if the individual lives in the capital city. Family income is categorized in 1-10 brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Having shown the increase in enrollment at teaching degrees around the scholarship cutoff, a key question that arises is: what do this students come from? Table 5 shows the RD estimates by field of studies, plus and option for not enrolling. Results show that students substitute away from the outside option (not enrolling) and from a social sciences degree, while I find no effect statistically different from 0 for the rest of the fields of study. Additionally, this results in enrollment could be driven by two different application behaviors: first, students could be adding a teaching degree option in their ranked-order list, and end up being assigned to that option. Second, students could be listing a teaching degree as their top choice, either moving up in the ranking or from not listing it at all. I test this alternative hypotheses by performing the RD analysis on both behaviors, for students who submitted ranked-order lists on the centralized platform. Results are shown in table 6. The observed increase in enrollment at teaching degrees is driven by more students ranking teaching degrees as their top-choice, and not just adding it in their lists in any position (as a backup, for example).

Table 5: RD estimates by field, 600 points cutoff

	(1) Estimate	(2) SE	(3) Observations	(4) Bandwidth	(5) Baseline
Education (Participant)	0.0366***	(0.00633)	42674	36.3	.086
Education (Non-Participant)	–0.00288	(0.00224)	42674	36.1	.014
Not enrolled	–0.0148*	(0.00780)	46368	39.9	.198
Social Sciences	–0.0132***	(0.00503)	54236	46.2	.083
Business	–0.00181	(0.00493)	57034	48.9	.082
Farming	–0.000733	(0.00278)	61931	53.2	.023
Art and Architecture	–0.000730	(0.00359)	71132	61.4	.049
Basic Sciences	0.00130	(0.00356)	47811	40.9	.028
Law	–0.000570	(0.00368)	57638	49.1	.038
Humanities	–0.00140	(0.00191)	58173	50	.011
Health	–0.00503	(0.00602)	76918	66	.169
Technology	0.00153	(0.00765)	54236	46.2	.203

Notes: This table shows the estimates from the RD design. Estimation is based on the sample of full test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing MSE.
*** p < 0.01, ** p< 0.05, * p<0.1

Table 6: RD estimates of application at teacher colleges

	Any choice		First choice	
	(1)	(2)	(3)	(4)
Applied	0.01332	0.01568	0.03210***	0.02469***
	(0.00980)	(0.01263)	(0.00630)	(0.00872)
Cutoff	600	700	600	700
Observations	33800	8752	48264	8752
Bandwidth	28.9	26.8	41.2	26.9
Mean Below	.220	.098	.106	.039

Notes: This table shows the estimate for the RD design. In Columns 1 and 2 the dependent variable is a dummy which takes value 1 if the student listed any teaching degree in their ranked-order list, while in Columns 3 and 4 the dummy variable takes value 1 if student ranked a teaching degree as his top choice.
*** p < 0.01, ** p< 0.05, * p<0.1

In the Chilean higher education market, It's common to retake the college entrance exam to enter a desired degree, and approximately 20% of entering students retake the test the following year. The results found in Table 3 could be biased if student delay their entry by retaking the exam the following year, in pursue of scoring above the scholarship threshold. I test this by performing and RD analysis on the probability of retaking the exam the next year. Results are shown in Table 7. The estimates show no significant effect on retaking behavior.

Table 7: RD estimates of retaking PSU

	(1)	(2)
Retake	-0.00715	-0.01186
	(0.00758)	(0.01545)
Cutoff	600	700
Observations	58627	17009
Bandwidth	50.4	47.5
Mean Below	.228	.251

NOTES: This table shows the estimate for the RD design, where the dependent variable is binary and takes value 1 if a student retakes the college entrance exam the next year, and 0 otherwise. *** $p < 0.01$, ** $p < 0.05$, * $p<0.1$

I also perform four placebo tests on the results found in Table 3. Results are shown in Table 8. The first column shows the result from the RD estimation on the 550 points threshold for the 50% richest students. The biggest scholarship at that point in time, called *Beca Bicentenario*, would fully cover tuition for students located in quintiles 1 and 2 of the income distribution, in any degree of an institution who participated inside the centralized admission system. However, richer students weren't eligible, and there was no other reason to expect a jump in teaching enrollment. In column 2, the RD regression is performed for every student at the 650 threshold, a value that does not make a student eligible to any scholarship. Columns 3 and 4 are the results for the 600 and 700 point thresholds in year 2010, before the program was implemented. As expected, I dont' find an effect in none of the cases.

Lastly, in Tables B1-B6 of the appendix I show that the results in Table 3 are robust to different estimation specifications, such as covariate controls, the bandwidth chosen and the specification of $f(.)$.

4.2 Labor market effects

The previous section showed that the policy attracted better students to the teaching profession. However, the policy's ultimate goal was to raise teacher quality, and the correspondence

Table 8: Placebo tests

	2011		2010	
	(1)	(2)	(3)	(4)
Enrollment	-0.00316	0.00010	-0.00302	-0.00063
	(0.00470)	(0.00786)	(0.00646)	(0.00527)
Cutoff	550	650	600	700
Observations	52540	20802	47246	11660
Bandwidth	67.8	29.2	50.2	38.4

NOTES: This table shows the estimates from four placebo tests. Estimation is based on the sample of full test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing MSE.
*** p < 0.01, ** p< 0.05, * p<0.1

between being a good student (in terms of test scores) and a good teacher is not straightforward. I study this question by performing a Differences-in-Difference (DID) analysis. In particular, I estimate the following equation:

$$Y_{ijt} = \alpha_1 \text{ParticipantDegree}_i + \alpha_2 \text{ParticipantDegree}_i \times \text{Post}_t + X_i' \alpha_x + \mu_t + \epsilon_{ijc} \tag{2}$$

where Y_{it} is a particular outcome for teacher i who enrolled in degree j in year t. The dummy variable *ParticipantDegree* takes value 1 if the teacher enrolled in a BVP-participant degree and 0 if not. The post dummy stands for post 2011 cohorts, X_i includes sociodemographic characteristics and μ_t are year fixed effects. The error term ϵ_{ijt} is clustered at the school level.

As outcomes, I use two measures of teacher effectiveness. The first one is teacher value added (TVA), which I compute (following Chetty et al., 2014, Araujo et al., 2016 and Bau and Das, 2020) from the equation:

$$y_{isjgt} = \sum_a \beta_a y_{i,t-1} I_{it}(\text{grade} = a) + \gamma_j + \delta_s + \alpha_t + \mu_g + \eta_{isjgt} \tag{3}$$

where an outcome for student i in school s, who received instruction by teacher j in class g and year t depends on his past achievement and a series of fixed effects, where I interpret a teacher's fixed effect as his value added. I compute mathematics teacher value added measures for 6th and 8th grade students, from 2013 to 2017. In order to control from learning-by-doing effects, or returns to experience, I restrict the subsample to just-graduated teachers, which corresponds to 2008-2012 cohorts (from one year pre-policy until two years post-policy).

The second measure of effectiveness comes from teacher evaluations performed by the ministry of education. It's a mandatory assessment for public school teachers, and they are evaluated in pedagogical decisions, teaching skills and classroom practices. The evaluation is high stakes, as good performance might imply a monetary bonus, while repeated underperformance leads to firing decisions. The evaluation comprehends two modules. In the first one, the teachers design a class defining its contents and evaluation, and they are later asked about teaching practices. The second one involves a videotaped class followed by questionnaires on students' behavior and teachers' performance. For this measure, the estimating sample are primary school teachers in public schools for the period 2011-2019. Both TVA and Teacher Evaluation measures were normalized to have mean 0 and standard deviation 1, so estimates are interpreted in SD sizes.

Table 9 shows the result of the DID estimation. For math TVA I find that teachers who studied in a Participant Degree are on average better, something expected as the most prestigious universities are the ones who participated. However, the gap between teachers from Participant versus non Participant degrees widens for post-policy cohorts, by a magnitude of 0.112SD. For the teacher evaluation, the estimated effect is of 0.119SD.

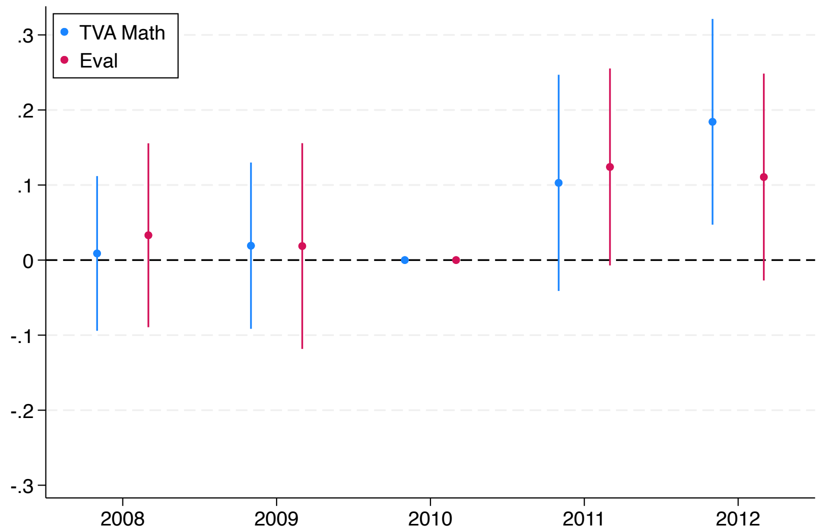
Table 9: DID estimates of performance

	(1) Math TVA	(2) Teacher Eval
ParticipantDegree	0.120***	0.158***
	(0.025)	(0.026)
Post=1 × ParticipantDegree=1	0.112***	0.119***
	(0.041)	(0.043)
Constant	-0.984***	-0.079***
	(0.012)	(0.013)
Observations	1774	9628

NOTES: This table shows the estimates from the Difference-in-Differences regression on labor market outcomes. In columns (1) the sample is composed of just-graduated 6th and 8th grade teachers from the 2008-2012 cohorts. In column (2), the sample includes every just-graduated primary school teachers for the period 2011-2019 (cohorts 2007 to 2015). In all cases, robust standard errors are computed.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

There exist several threats to identification. One is due to the endogenous decision of universities to participate in the policy on a degree-by-degree basis. However, the participation decision is fixed by the time the students make their enrollment decisions. Under this analysis, the decision process by universities is not relevant for the validity of the analysis, as only the enrollment decisions over time are relevant. Moreover, the estimates are robust to different group specifications, such as choosing the top 5 or top 10 universities. A second threat would be the existence of pre-policy differential trends between and not participating degrees that could explain the expanding gap post policy. Figure 5 shows the event-study design of the policy, which rules out the existence of such trends. Lastly, a third threat could be due to transition between groups which implies a SUTVA (Stable Unit Treatment Value Assignment) violation. I argue that the policy implied a positive spillover to non-participating degrees: the influx of higher performing students from non-teaching to participant degrees put stress to admission thresholds, and students who didn't make the new cutoffs at top institutions moved to non-participating degrees, raising the average quality of students. As the policy had a positive effect on the control group, I interpret the results as a lower bound of the true effect. Further, two additional evidence go against the existence of such transitions. Figure 5 shows that, at the threshold, there is no substitution away from non-partitipant degrees. While there could be substitution along the whole distribution of test scores, Figures 2a and 2b show that, while the distribution of test scores of studens enrolling in participating degrees shifted due to the double component of the policy, the distribution of test scores of students enrolling in non-participating degrees remained unchanged.

Figure 5: Event Study



Notes: This figure shows the result of the event-study design of the difference in performance over time of students enrolling participating and non-participating degrees. For Math Teacher Value Added, the sample is composed of just-graduated 6th and 8th grade teachers from the 2008-2012 cohorts. For the Teacher Evaluation measure, the sample includes every just-graduated primary school teachers for the period 2011-2019 (cohorts 2007 to 2015). In all cases, robust standard errors are computed. Point estimates as well as 95% confidence intervals are shown.

5 Model

In the previous section I showed that the policy managed to raise the quality of students at teaching degrees by attracting the higher and restricting the lower scorers. This increase of high-quality students translated into better teachers upon graduation. However, my identification strategy for enrollment (RD) only allowed me to estimate a local effect around an eligibility cutoff. To extrapolate and to better understand the mechanisms that drive the observed equilibrium, I build an equilibrium model of higher education within a centralized admission system, where the government sets policies for degrees, colleges make a joint discrete-continuous choice (policy participation and tuition setting), and students choose the college-degree combination that maximizes their utility. The model is then used to simulate the equilibrium effects of counterfactual policies.

5.1 Environment

There exists a set $\mathcal{I}$ of individuals such that $i \in \mathcal{I} = \{1, ..., n\}$, and a set $\mathcal{J}$ of college degree programs (both targeted and non-targeted) within a centralized admission platform, such that $j \in \mathcal{J} = \{1, ..., J\}$, where $j = 0$ is the outside option and includes enrolling in an out-of-platform degree, or not attending college at all. Within each period $t = \{1, ..., T\}$, the timing is as follows:

1. The government announces $P = (\mathcal{E}, \mathcal{F}, m)$ for every degree in the platform.
2. Colleges make a joint decision of participation and tuition setting for their degrees.
3. Students observe P and the listed degrees and submit ranked ordered lists.
4. The centralized system matches students to degrees.

Now I describe the setting of the centralized admission system, which I model closely following the literature (Azevedo and Leshno, 2016, Abdulkadiroğlu et al., 2017) but adapting it to the chilean context. Students have a preference order $\succ_i$ over degrees. Colleges make admission decisions solely based on an index score s_i that is composed of a student's multiple observable characteristics. The composition of this index is common knowledge. Colleges might not admit every applicant in their degrees, either because they operate in capacity restrictions or they impose an index cutoff, so there exists a vector $v = (v_0, ..., v_J)$ of non-negative elements, where a_j specifies the vacancies for degree j, and $v_0 = \infty$. In determining enrollment, a student is characterized by his preference order and score, ie $\psi_i = (\succ_i, s_i)$. The rules set by the government imply that a student can only apply to degrees for which $f_{ij} = 1$ and, if enrolled, they will receive funding according to e_{ij}.

The centralized admission process implements a deferred acceptance algorithm. I define the mechanism $\phi(\psi, v) = \mu$, where μ is the matching generated given students' types and colleges' vacancies per degree. The algorithm ensures that each student is assigned his most preferred degree among the available ones (those who haven't been filled by higher scoring students), and that every degree gets an assignment no bigger than its capacity constraint. The matching endogenously determines a $J \times 1$ vector of score cutoffs $c(\mu)$ such that market clears[4]. The feasible choice set for student i is $\Omega_i(\mu) = \{j \in \mathcal{J} | s_i > c_j(\mu)\}$, and $D_i(\mu)$ is the preferred choice within the feasible set. The algorithm implies $D_i(\mu) = \mu(\psi_i)$.

[4]Note that the mechanism doesn't imply that every student will be admitted into a program: if a student does not score above any cutoff, he'll take the outside option (his choice set is a singleton).

5.2 Demand

Students are utility-maximizing agents who choose a college-degree combination (denoted program) among available ones by trading off different attributes such as quality, distance and out-of-pocket fees[5]. A student i's indirect utility for attending program j is given by:

$$u_{ij} = u(z_i, x_j, w_{ij}, \epsilon_{ij}; \theta) \tag{4}$$

where z_i and x_j are vectors of student and programs characteristics, respectively. The vector w_{ij} denotes match characteristics, such as the distance from student i to the campus where program j is located. I further parameterize the utility function as linear in the students and programs' observable and unobservable characteristics, taking the form:

$$\begin{aligned} u_{ij} &= V_{ij} + \epsilon_{ij} \\ &= q_j + \alpha_p op_{ij} + \alpha_w w_{ij} + \alpha_z z_i + \alpha_c x_j z_i + \epsilon_{ij} \end{aligned} \tag{5}$$

where q_j is the quality of program j and is further defined as:

$$q_j = \delta_j + \alpha_a \bar{A}_j \tag{6}$$

The parameter δ_j includes time-invariant program characteristics (both observed and unobserved), while $\bar{A}_j$ is the average ability level of students enrolled in degree j. The variable op_{ij} are the out-of-pocket fees faced by student i for program j, which will depend on the ongoing policy such that $op_{ij} = (1 - \lambda_{ij})p_j$. The utility of the outside option (not enrolling) is normalized to zero. The idiosyncratic shock ϵ_{ij} is assumed to follow a type-1 extreme value distribution. The choice set Ω_i includes every degree with a cutoff below the student's program-specific score, and the probability that student i chooses degree j can be written as:

$$s_{ij} = \frac{\exp V_{ijt}}{\sum_{k \in \Omega_i} \exp V_{ikt}} \tag{7}$$

In my empirical application, z_i includes a constant, a student's average (between mathematics and language) test score, his mother's education level, an indicator variable for

[5]For ease of exposition, I omit the time subscript.

coming from a private high school, and the monetary value of the scholarship he's eligible to if enrolling in that program. w_{ij} includes a dummy which takes value 1 if the student lives in a different region than the program and the relative ability of student i to the average ability of students enrolled in program j. I interact out of pocket fees with the student's income[6], and peer's ability with test scores and income. Additionally, I include a third degree polynomial between a student's test score and an indicator if program j's field is Education, which will aid in the identification of the price coefficient.

5.3 Supply

Colleges compete in a static Bertrand differentiated product framework choosing policy participation $B_j \in \{0,1\}$ and tuition p_j^b for all their offered degrees[7], where the supra index $b \in \{0,1\}$ denotes policy participation. Naturally, $b=0$ for every non-targeted program and, if participation is mandatory, then $b=1$ for every targeted program. I assume that colleges cannot choose quality, and variations between periods only happen through peer effects. Colleges are not allowed to price-discriminate, and the effective price paid by a student will only depend on his scholarship status. In each period, the colleges' joint profit maximization problem is given by:

$$\max_{\{B_j, p_j^b\}_{j \in \mathcal{F}_n}} \sum_{j \in \mathcal{F}_n} (\Pi_j(p) + v_j) \tag{8}$$

$$\Pi_j(p) \equiv \sum_{k=0}^{1} \left(\mathbb{1}\{B_j = k\} \cdot \sum_{i \in \mathcal{I}} (s_{ij}(op_{ij}^k, op_{i,-j}) \cdot [p_j^k - m_j^k]) \right) \tag{9}$$

where $\mathcal{F}_n$ is the set of degrees offered by college n, $B_j \in \{0,1\}$ is the policy participation decision, p_j^b the counterfactual price for degree j under participation decision b, and m_j^b are the marginal costs. The probability that student i enrolls in program j, denoted s_{ij}, depends on the out of pocket fees of all degrees in i's feasible choice set. A college can only influence enrollment in one of his degrees via participation and tuition setting, and the discrete choice B_j will affect both the price-setting behavior of colleges and the out-of-pocket fees faced by students, because while colleges set unique prices for degrees, scholarship holders have their tuition partially or fully covered by the government. Therefore, the out-of-pocket fees faced by student i is:

[6]As test scores are the running variable for the discontinuity generated by the policy, I cannot interact prices with test scores.

[7]For ease of exposition, I suppress the time sub-index t in this section.

$$op^b_{ij} = \begin{cases} p^0_j & \text{if } B_j = 0 \\ (1-\lambda_{ij})p^1_j & \text{if } B_j = 1 \end{cases} \tag{10}$$

Where $\lambda_i \in [0,1]$ specifies the degree of tuition coverage. The one-price policy limits what colleges can charge. In the case of full coverage, students' utilities are unaffected by price changes, and therefore colleges have the incentive to raise tuition. However, only a fraction of students are scholarship holders[8], and they would risk losing enrollment from non-scholarship holders who would prefer to enroll in a different program.

5.4 Policy space

In the pursue of targeting students to certain degrees, the government can implement variations of e, f and m, which will impact several equilibrium objects. I define the counterfactual feasible choice set $\Omega^*_i(\mu) = \{j \in \mathcal{J} | s_{ij} > c^*_j(\mu)\}$, the set of eligible degrees under counterfactual cutoff scores $c^*_j(\mu)$ and government rules P^*. The counterfactual feasible choice set is the result of multiple transition patterns, including people coming into/out of the targeted degree, a non-targeted degree or the outside option. The alternative set of rules P^* also generates a counterfactual $\succ^*_i$ as not only the feasible choice sets are altered but also the students' preference order, given a new set of equilibrium prices p^*. The preferred choice, then, can differ both because of different eligible degrees and a different ordering of them. In general, the centralized admission process will generate a different matching, that is, $\phi(\psi, v) = \mu \neq \mu^* = \phi(\psi^*, v)$.

5.5 Equilibrium

The characteristics of the centralized admission system imply that the equilibrium is a fixed point of the mapping $\phi(\psi, v)$. The equilibrium is defined such that no student-program pair that would like to break from their current match to re-match to each other, and the deferred acceptance algorithm generates a stable matching. Azevedo and Leshno (2016) show that the equilibrium is unique and that the mapping is continuous.

For the supply side, colleges need to solve a complex problem, as they need to anticipate the price equilibrium in each of the 2^N counterfactual market structures (given by their policy participation decisions). Even in my setup, where the policy is limited to teacher colleges,

[8] Less than half of the cohort for the most prestigious Teacher college in the implementation year.

there are 60 education programs and computing 2^{60} market structures is computationally infeasible (both for players and the econometrician). Therefore, I depart from the standard Nash Equilibrium and assume players' action depend only on their close rivals' best responses. This is similar to the concept of Oblivious Equilibrium (Weintraub et al., 2008). However, my model is static and there is not a clear industry leader, as the education market is sparse and colleges compete to attract students with different characteristics. Therefore, the participation decision decision solves:

$$B_j^* = \arg \max_{B_j \in \{0,1\}} \pi_j(B_j, B_{-j}^R)$$

Where the supraindex R denotes the players' close rivals. In equilibrium, each player correctly predicts the decisions of his close rivals. The notion of close rivals is defined by the cross-price elasticities of demand, speficically, the close rivals of program j is the set of programs with the highest ds_j/dp_k. However, it includes only programs that participate in the discrete decision (policy participation), while every program is considered while making the conntinuous choice (prices). This notion not only reduces the dimensionality of the problem but also might better capture the heuristic behavior of colleges. In particular, it captures the fact that decisions of "distant" competitors could have a close to null impact on a player's profits, and so is neglected when deciding on participation. A crucial concern is the number of rivals that are considered as "close". Since I have a panel of data, I can use my demand and supply estimation to predict the decision of each player for any year. Therefore, my strategy implies predicting colleges' behavior assuming different notions of equilibrium, and staying with the one that yields a better fit to the data. In my application, the number of close rivals is the one who minimizes the sum of square deviations between the predicted and observed profits of education programs.

5.6 Identification

I estimate the parameters $\alpha = (\alpha_a, \alpha_p, \alpha_w, \alpha_z, \alpha_c)$ and δ_j via Simulated Maximum Likelihood. In my model, both the prices p and peers' ability $\bar{A}$ are equilibrium outcomes, and therefore a standard regression would yield biased estimates. I follow the standard pratices of demand estimation with unobserved heterogeneity (Berry et al., 1995) which relies on using instrumental variables. I adress the endogeneity problem of prices by exploiting the discontinuity generated by the policy. At the scholarship threshold, the only difference between students who score just above and below the cutoff is the scholarship eligibility, and therefore the out of pocket tuition they face. The difference in enrollment around the cutoff is explained by the exogenous variation in out ouf pocket tuition, and its associated price (dis)utility. This strategy was also used by Kapor et al. (2022) and Larroucau and Ríos (2024). For the average ability at program j, I construct instruments based on local demographics and market structure, typical in the Industrial Organization literature. The standard exclusion restriction requires that these characteristics are orthogonal to both demand and cost current unobservables, which is plausible if geographical sorting is pre-determined and colleges' decisions are made before the admission process. The validity condition requires that these characteristics should be correlated with the test scores of students enrolled on a given program. The geographical variation of students' test scores, combined with the dis-utility of distance to the campus of a given program should (partly) explain the average test scores of said program. At the same time, the number of rival program within that region, and its quaility, should also affect the average test scores of students enrolled in that individual program. This strategy is common in the education literature, used (among others), by Allende (2019) and Gazmuri et al. (2016). From the supply side, marginal costs are recovered from the pricing equation of colleges, derived from the first order condition of their profit-maximizing problem. Participation decisions are not estimated, but determined in equilibrium, both in the observed and in the counterfactual exercises.

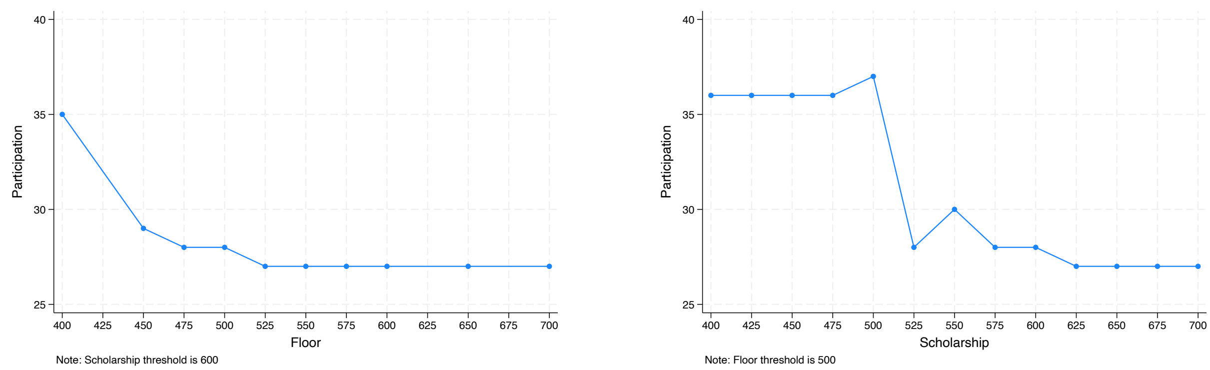
6 Results

6.1 Counterfactual exercises

To study the effect of each individual component in isolation, first I simulate counterfactual scenarios varying the floor while keeping the observed scholarship threshold, and viceversa. Results can be found in Figures 6, 7 and 8. The first one shows the participation decision of all Education programs under counterfactual floor (Subfigure 6a) and scholarship threshold (Subfigure 6b) rules. First note that in any case, participation doesn't go below 27. That is because programs that participate in the centralized platform were required to participate. As I don't model exit, these programs will remain even though for inplausible high floor values they will lose all enrollment and operate under a deficit. Therefore, these Figures serve to delimit the region of plausible policy rules. For the Floor counterfactuals, participation drops sharply, and no program chooses to freely participate for values above 525. For the scholarship value, however, the effect is mor gradual. Starting from low values, It's the lowest quality universities that quickly lose interest in participating in the policy, as they will fail to attract students with high enough scores, and they trade off the decreasing enrollment implied by the Floor. For values above 625, every university that freely chooses to participate, determines that the lost revenue from the floor is not ofset by the additional students they would enroll because of the scholarship.

Figure 6: Simulations: Participation

(a) **(b)**

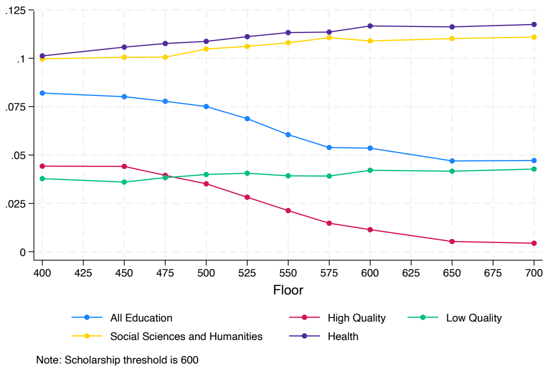


NOTES: These figures show the participation decision of Education programs under counterfactual policy rules. Subfigure 6a shows the effect of varying the floor while keeping the scholarship threshold constant, while Subfigure 6b shows the effect of varying the scholarship threshold while keeping the floor constant.

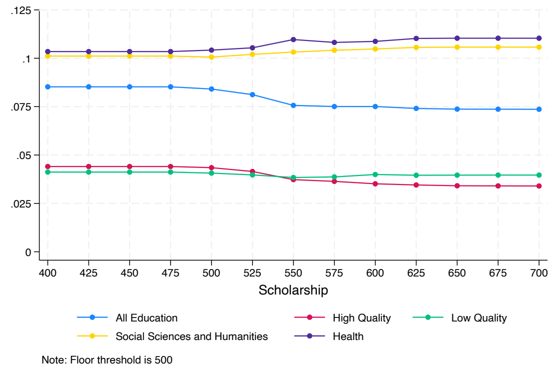
Figure 7 shows the effect of the policy on the market shares of different groups of programs. Subfigure 7a shows the effect of varying the floor while keeping the scholarship threshold constant, while Subfigure 7b shows the effect of varying the scholarship threshold while keeping the floor constant. It can be shown from 7a that the lower-quality Education programs preserve mostly a constant market share, as they quickly opt-out from the policy, and they don't suceed in capturing students from other fields. The high-quality education programs mostly are forced to remain, and therefore loose market share, virtually dropping to zero for an extremely high floor of 700 points (top 5% of the exam distribution). Students from high-quality education programs substitute away to other fields such as Social Sciences or Health. From 6b it can be seen that the decline of market shares is less severe, as the high-quality programs are able to retain most of their students, while failing to attract new ones for high scholarship thresholds.

Figure 7: Simulations: Market Shares

(a)



(b)

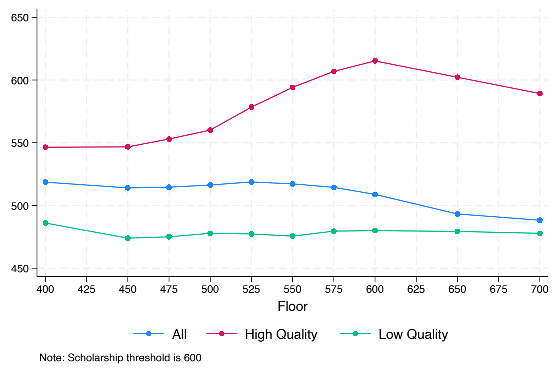


NOTES: These figures show the market shares of different set of programs under counterfactual policy rules. Subfigure 6a shows the effect of varying the floor while keeping the scholarship threshold constant, while Subfigure 6b shows the effect of varying the scholarship threshold while keeping the floor constant.

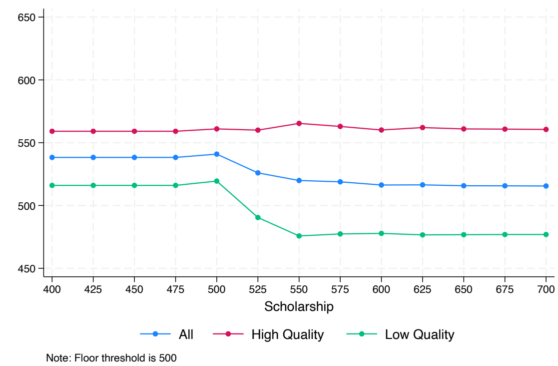
Figure 8 shows the average test scores of Education programs under counterfactual policy rules. Subfigure 8a shows that average test scores in high-quality programs raises sharply with the floor, as they are forced to remain in the policy and their market shares decline rapidly. The decline after 600 is explained by two out-of-platform, high-quality programs that opt-out of the policy at the 600 and 650 thresholds, respectively. Overall, while average test scores remain mostly constant, because the higher scores of participating programs if offset with their decline share of the aggregate Education market share. For the scholarship counterfactuals, the decline in test scores coincides with low-quality programs opting-out, since they fail to attract students with high enough scores. The high-quality programs, however, are able to retain most of their students, and therefore their average test scores remain mostly constant.

Figure 8: Simulations: Test Scores

(a)



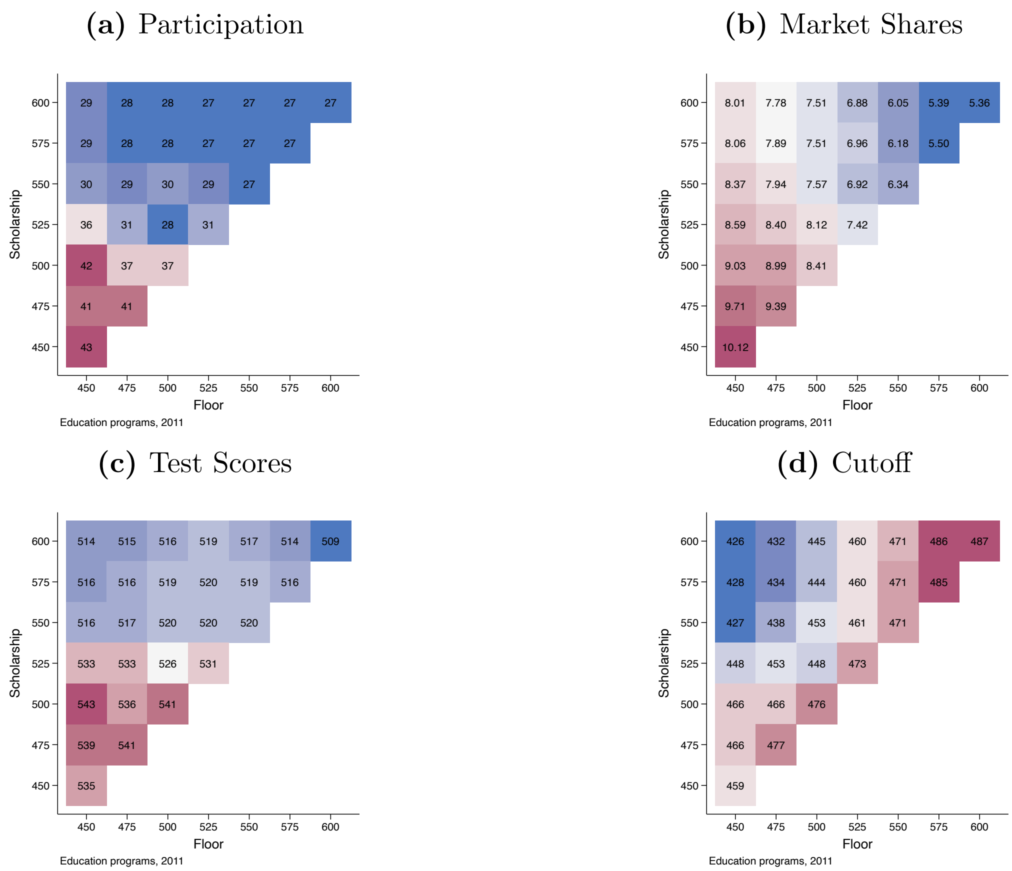
(b)



NOTES: These figures show the average test scores of Education programs under counterfactual policy rules. Subfigure 6a shows the effect of varying the floor while keeping the scholarship threshold constant, while Subfigure 6b shows the effect of varying the scholarship threshold while keeping the floor constant.

While Figures 6, 7 and 8 are useful to analyze the effect of each individual component in isolation, there is no reason to keep one of them fixed in reality. Therefore I proceed to simulate a grid of counterfactual policy rules, which can be found in Figure 9. I omit simulations for scholarship parameters below floor parameters, as they generate virtually the same equilibrium as in the case they are equal. Subfigure 9a shows that participation varies dramatically over the policy configuration, as almost all Education Programs opt-in, while for a considerable region only forced programs participate. Subfigure 7a show that Market Shares find their maximum for the lowest combination of floor and scholarship parameters, while their minimum (roughly half), for the highest floor-scholarship combination. The case of test scores, which can be seen in Subfigure 9c is non-monotonic. The maximum can be found for the $\{450; 400\}$ combination. For scholarship parameters below that point, programs are effectively attracting below-average students, while for higher scholarship parameters many programs start to opt-out, as they fail to attract enough good students to compensate the lost enrollment. This combination implies an increase both in average test scores and in market shares compared to the observed policy. However, this configuration will be dramatically costlier, as most of the students pursuing Education degrees would have a full scholarship, therefore the policy maker should trade-off quantity, quality and cost in deciding the optimal policy.

Figure 9: Simulations: Grid



NOTES: This figure shows the results of counterfactual simulations under a grid of policy parameters. 9a shows the participation decision of Education programs, 9b shows the market shares of different groups of programs, 9c shows the average test scores of Education programs, and 9d shows the cutoff scores of Education programs.

7 Conclusion

This paper studies the effects of targeted policies in higher education. I present a framework for the type of policies upon consideration, based on two instruments the government can set: (i) an eligibility rule for public funding, being of the form of tuition coverage and direct transfers, and (ii) a rule that restricts students from enrolling in certain degrees. I present a case within that framework, a policy launched in Chile that aims to increase teacher quality by crowding in high performing students to Education degrees, while crowding out low performing ones. I present causal evidence that the policy managed to increase the enrollment of high performing students at teaching degrees. My regression discontinuity estimates find that students who score just above the eligibility cutoff have a 30% higher probability of enrollment. Moreover, this increase in better performance has a posterior corresponde in the labor market, as the gap in teacher effectiveness between Participant and non-Participant programs widens for post-policy cohorts. To better understand the mechanisms that drive the observed equilibrium, I build a supply and demand model of higher education, where the government sets policies for degrees, colleges decide on participation and tuition, and students make college-major choices. Simulation exercises shown that alternative policies could achieve a higher overall effect, at the expense of either a higher fiscal burden or a reduction in graduates from Education degrees.

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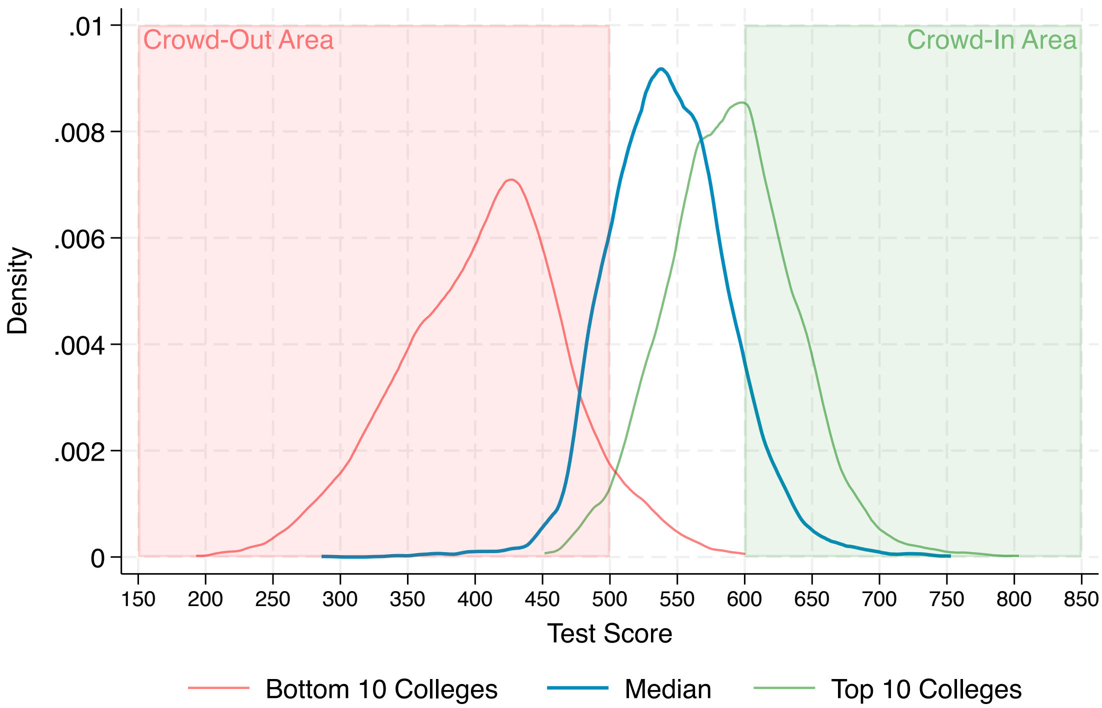
A Appendix: Descriptives

Figure A1: Test score distrubtion, teacher colleges



NOTES: These figure show the distribution of test scores for different groups of teacher colleges, in the year before the policy was implemented.

B Appendix: RD

Table B1: RD estimates of teacher enrollment, epanechnikov kernel

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05209***	0.03807***	0.02480***	-0.01860***	-0.00264	0.00132
	(0.00273)	(0.00618)	(0.00915)	(0.00317)	(0.00220)	(0.00080)
Cutoff	500	600	700	500	600	700
Observations	71160	41872	7975	92630	40859	16389
Bandwidth	40	35.9	24	52.9	34.7	46.1

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B2: RD estimates of teacher enrollment, uniform kernel

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05149***	0.04001***	0.02167**	-0.01805***	-0.00119	0.00137
	(0.00278)	(0.00613)	(0.00963)	(0.00351)	(0.00177)	(0.00095)
Cutoff	500	600	700	500	600	700
Observations	63218	37838	6250	67172	58173	14835
Bandwidth	35.2	32	19.3	37.7	49.9	42.3

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B3: RD estimates of teacher enrollment, with controls

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05192***	0.03431***	0.02415**	-0.01759***	-0.00242	0.00113
	(0.00281)	(0.00675)	(0.00976)	(0.00316)	(0.00227)	(0.00083)
Cutoff	500	600	700	500	600	700
Observations	71305	37155	7857	99297	40425	14795
Bandwidth	42	33.8	26.9	60.7	37	46.3

NOTES: Controls include mother's education, family income and region. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B4: RD estimates of teacher enrollment, extended controls

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05209***	0.03578***	0.02407***	-0.01807***	-0.00307	0.00123
	(0.00268)	(0.00622)	(0.00892)	(0.00306)	(0.00224)	(0.00076)
Cutoff	500	600	700	500	600	700
Observations	78258	42932	8633	104921	41872	15602
Bandwidth	44.1	36.9	26.5	60.8	36	44.5

NOTES: This regressions control for: Female, High School GPA, Public HS, Voucher HS, Private HS, Santiago, Family Income, Private Health, Father With College, Mother With College, Father Employed, Mother Employed. *** p < 0.01, ** p< 0.05, * p<0.1

Table B5: RD estimates of teacher enrollment, Bandwith 50

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05252***	0.04033***	0.01661**	-0.01760***	-0.00216	0.00100
	(0.00254)	(0.00543)	(0.00657)	(0.00337)	(0.00190)	(0.00074)
Cutoff	500	600	700	500	600	700
Observations	87686	58173	17882	87686	58173	17882
Bandwidth	50	50	50	50	50	50

*** p < 0.01, ** p< 0.05, * p<0.1

Table B6: RD estimates of teacher enrollment, Bandwith 25

	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05290***	0.03122***	0.02481***	-0.01588	-0.00361	0.00023
	(0.00351)	(0.00758)	(0.00929)	(0.01729)	(0.00272)	(0.00059)
Cutoff	250	600	700	250	600	700
Observations	44732	28894	8151	1271	28894	8151
Bandwidth	25	25	25	25	25	25

*** p < 0.01, ** p< 0.05, * p<0.1