Optimal Policy Design for Teacher Recruitment*

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Abstract

This paper studies the design of higher education policies targeted at improving teacher recruitment. I leverage the introduction of a policy in Chile that aimed to raise teacher quality by crowding-in higher performing students into Education programs, while crowding-out the lower-performing ones. Exploiting the sharp assignment rule I estimate that, at the threshold, enrollment of high performing students at teacher colleges increased by 42%, with low-income students coming disproportionately from non-enrollment. The policy generated a positive composition effect of 0.25SD in test scores, which lead to an increase in 0.11SD in Teacher Value Added and 0.12SD in Teaching Skills. I develop a demand and supply model of the higher education market. In doing so, I present a novel method for solving discrete-continuous games in large markets. Simulation of counterfactual policies lead to increases of up to 6.6% in the test scores of students enrolled at teacher colleges, and up to 27% in Teacher Value Added. A policy targeted at low-income students can yield further gains in Teacher Value Added at no additional cost.

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1 Introduction

The challenge of raising the quality of public servants is central to strengthening state capacity and effective public service delivery. This is because government institutional performance depends not only on rules and structures, but critically on the selection and retention of capable individuals (Finan et al., 2017). However, employment in the public sector is characterized by rigid hiring rules and pay scales[1] (Shleifer and Vishny, 1994, Evans, 1995), limited use of performance-based incentives,[2] (Holmstrom & Milgrom, 1987), below-market wages, weak accountability and limited opportunities for professional growth (Besley et al., 2022), deterring high-ability candidates. Beyond adverse selection, an additional market failure can be found at the higher education stage, as training is partially provided by private institutions that don't internalize the social benefits of having high-quality public servants.

The teaching profession illustrates the personnel challenges faced by the public sector. Teachers are one of the largest groups of public employees and are central to the development of human capital and long-term socioeconomic outcomes (Chetty et al., 2014a, Chetty et al., 2014b, Hanushek, 2020). Most research on teacher recruitment has focused on wage-related policies (Behrman et al., 2016, Biasi, 2021, Tincani, 2021), often neglecting the upstream role of higher education in shaping the pool of potential teachers. However, research on higher education finance centers on the equity and efficiency of different funding instruments (Angrist et al., 2014, Cohodes and Goodman, 2014, Solis, 2017, Londoño-Vélez et al., 2020), ignoring how educational policy can direct talent into strategic fields.

This paper fills this gap in the literature by studying the optimal design of an educational policy for improving teacher recruitment. I use rich administrative data, quasi-experimental policy variation, a supply and demand model of the higher education market, and a potential outcomes model to show how the combination of financial incentives and selectivity measures can improve the pool of students that enroll at teacher colleges, and how this translates into better teachers.

To answer this research question, I proceed in four steps. First, I use data on the universe of elementary students, college students and teachers in Chile to document a positive relationship between the university entrance exam score and subsequent measures

[1] An incumbent politician might seek to fill up public jobs with political supporters, or benefit them with higher wages, although ideological misalignment between politicians and bureaucrats can negatively impact performance (Spenkuch et al., 2023).

[2] Incentives can make public servants reduce effort in their non-incentivized tasks.

of teacher effectiveness. Second, I provide causal evidence that a policy intervention successfully attracted higher-performing students into teaching programs and improved the quality of new teachers. Third, I develop a structural model of the higher education market that incorporates endogenous responses from both universities and students. Finally, I estimate the model and use it to simulate counterfactual policy designs, identifying the configurations that most effectively improve teacher recruitment and quality.

The Chilean context offers a unique setting to study the selection into the teaching profession, thanks to both rich administrative data and a well-defined policy intervention. First, I leverage a unique combination of linked administrative datasets that allow me to track students from their university application stage, through college, and into the labor market if they become teachers. Second, a 2011 policy introduced both incentives and selectivity measures to improve the pool of entrants into teaching programs.

The policy in question is *Beca Vocación de Profesor* and involves two main components. First, students who scored above the 80th percentile on the University Entrance Exam were eligible for a scholarship that fully covered tuition and fees. Second, participating universities were required to set a minimum admission score at the median of the exam distribution, restricting enrollment of lower-scoring students. The program was established in public universities, while private colleges were given the option to participate. Financial incentives affect choices on both sides of the market: on the demand side, the scholarship aims to lower financial barriers and attract high-performing candidates into teaching programs; on the supply side, private universities must decide on take-up by weighing the potential loss of enrollment from stricter admission standards against the increased demand generated by the scholarship.

I estimate Teacher Value Added (TVA) following standard practices in the education literature (Chetty et al., 2014a, Bacher-Hicks and Koedel, 2023). In addition, the National Teacher Evaluation Program was specifically designed to measure teaching skills and classroom practices. A simple regression yields that a 1 standard deviation (SD) increase in the average between the language and mathematics component of the university entrance exam is associated with a 0.21SD in TVA and 0.18SD in teaching skills, a result consistent with the literature, which finds a moderate link between academic achievement and classroom effectiveness (Jackson et al., 2014).

The sharp eligibility rule for the scholarship provides a credible source of variation to estimate the treatment effect on enrollment at the threshold. Using a regression discontinuity (RD) design, I find that students just above the cutoff are 42% more likely to enroll in a teaching program. There is also substantial heterogeneity: for low-income students, the effect is twice as large as for high-income students, and most of the increase comes from students who would otherwise not enroll in higher education. For high-income students, the increase is driven entirely by substitution from other fields. These results reveals features that can lead to efficiency gains in policy design, and motivates the simulation of a counterfactual policy targeted at low-income students.

In order to assess the effect of the policy on teacher quality, I leverage comprehensive administrative data that track individuals both as students and later as teachers. Using a Differences-in-Differences (DID) approach, I compare teachers that graduated from participating and non-participating teaching degrees, for both pre-policy and post-policy cohorts. I find that the policy generated a positive compositional effect of 0.25 SD in the average test scores of students enrolled at participating teaching degrees, which led to a 0.11 SD increase in TVA and a 0.12 SD improvement in teaching skills.

Given the heterogeneity of teacher colleges, the optimal policy was ex-ante not obvious. A sufficiently high admission rule would make most universities opt out, reducing the overall impact of the program. A low enough admission rule would fail to crowd-out low ability students from selecting into the teaching profession. A high eligibility cutoff for the scholarship attracts few marginal students and makes the scheme unattractive for private colleges, while a low eligibility cutoff would make the program costlier and generate a negative composition effect. In practice, the take-up of the policy was low, as only 35% of private colleges decided to opt in.

While results show that the observed policy was successful in improving teacher recruitment, two things limit the analysis. First, the methods cannot decompose the relative influence of incentives and selectivity in the observed equilibrium. Second, the low participation rate among private colleges highlights the importance of accounting for general equilibrium effects in policy design. In addition, pricing decisions are crucial, as colleges are multi-product firms and education degrees can represent a significant share of total enrollment. The policy effectively introduces a shock to out-of-pocket expenses, which may prompt universities to adjust tuition not only for education degrees but also for other programs. Ignoring these supply-side responses can lead to misleading conclusions about the potential impacts of alternative policies.

For these reasons, I construct a demand and supply model of the higher education market. In each period, the government implements a policy by setting financial incentives and admission rules. Colleges solve a discrete-continuous problem: for their education degree, they decide whether to participate in the policy, while they simultaneously set tuition for every program they offer. Finally, students choose among college-degree pairs by weighing factors such as quality, distance, and out-of-pocket costs.

Solving for an equilibrium in discrete-continuous games has proven to be challenging due to the high dimensionality of the strategy space. A methodological contribution of this paper is the development of a novel equilibrium concept, which flexibly adapts to markets with a different number of players, and heterogeneous degree of concentration. Based on the notion of bounded rationality (Simon, 1955) it captures the fact that, as the number of player grows, players struggle to compute their payoffs for every possible equilibria, so they must rely on some simplifying heuristic. Within this approach, agents strategically interact by accurately predicting the actions of a subset of relevant rivals, while allowing for possible prediction errors of distant competitors. The set of "close rivals" is explicitly defined from cross-price elasticities derived from observed demand patterns, ensuring that strategic considerations reflect realistic competitive pressures rather than arbitrary classifications. I build a criterion function that determines the number of competitors that should be accounted for in strategic interactions.

This equilibrium concept offers three distinct advantages. First, by limiting strategic anticipation to a manageable subset of competitors, it significantly reduces computational complexity, thus enabling equilibrium analysis even in large-scale, heterogeneous markets. Second, it leverages market data to inform the selection of close rivals, providing a data-driven foundation for the extent of strategic sophistication in the model, and allowing it to accommodate diverse competitive structures ranging from highly segmented to concentrated markets. Third, the bounded rationality assumption better captures empirically observed decision-making heuristics: estimation of the criterion function rejects that colleges solve for a Nash equilibrium, and the function is minimized when colleges consider their four closest rivals.

The model allows me to estimate the enrollment distribution under counterfactual policy rules, and to measure the gains in terms of the sorting of students into teaching degrees. To measure the gains in teacher effectiveness, I need to estimate Degree Value Added (DVA), that is, the contribution of a degree to teacher effectiveness. Estimation of treatment effects in educational contexts is challenging because of selection bias, that is, students tend to self-select into programs based on their potential outcomes. While in K-12 education the sorting of students into schools is usually controlled by the use of prior test scores, such data is absent in the case of higher education. I address this issue by using a two-step control function approach (following Heckman, 1979) that allows to control for unobserved preference parameters that govern selection. Specifically, I use the multinomial logit selection model of Dubin and McFadden (1984) that allows to control both for selection on absolute advantages (high-ability students sort into high-ability degrees) and comparative advantages (a specific student-degree match effect).

Simulation of alternative policies show that participation decisions are highly sensible to the policy configuration: while a low score requirement for scholarship eligibility can induce participation of private colleges, a sufficiently strict admission rule will make most-programs opt-out, achieving a lower overall effect. At the same time, universities react to the increase in demand for teaching degrees by lowering tuition of other fields up to 10%. Estimation without considering supply-side responses will therefore tend to overestimate the true effect of the policy.

Counterfactual policy rules succeed in raising the quality of college students that pursue Education studies. Maximum gains are reached with a policy that is moderately selective and highly generous in its funding, leading to an increase of 6.6% in the Entry exam score of students at teacher colleges. Such a policy, which is targeted at maximizing pre-college achievement, will however reduce 6.8% the average Teacher Value Added. That is because most spare capacity comes from low quality teacher colleges, which produce below-average teachers. A policy that maximizes TVA must be highly selective: while take-up is reduced for private universities, the compositional changes in public colleges generate an overall positive effect. A means-based policy yields additional gains without increasing the overall cost, exploiting the fact that low income students have a higher price sensitivity, a higher preference for Education programs, and they are drawn disproportionately out of non-enrollment, attenuating price responses from non-education programs.

Related Literature This paper builds upon several strands of literature. It contributes to the literature of policies aimed at increasing teacher quality. Most of the literature have focused on in-the-job policies, such as reducing absenteeism (Duflo et al., 2012), formal training (Angrist and Lavy, 2001, Loyalka et al., 2019), peer mentoring (Rockoff, 2008) or performance payment (Muralidharan & Sundararaman, 2011). In so far as recruiting policies, there is evidence on the effect of increasing salaries (Tincani, 2014, Bobba et al., 2024) and flexible pay schemes (Biasi, 2021). There is also evidence on the effect of entry barriers, such as occupational licensing (Larsen et al., 2020). This article contributes by showing evidence on how the design of a higher educational policy can raise teacher quality. The results, however, extend to other professions where the public sector is the primary employer, such as healthcare providers.

It also 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). Notably, there is a significant gap in the effect of policies targeted at specific degrees. Neilson et al. (2022) studies the same teacher recruitment policy and use machine learning tools to study the effectiveness of alternative screening policies based on using additional pre-college characteristics. In contrast, I build a general equilibrium model to analyze the optimal policy rule based on the status-quo covariates.

Lastly, this paper also contributes to the literature on the estimation of discrete-continuous games. Most of the empirical industrial organization literature relies on moment-based equilibrium selection, such as cursed equilibrium (Eyster & Rabin, 2005) for static games and oblivious/partially oblivious equilibrium (Weintraub et al., 2008, Benkard et al., 2015) for dynamic games. While this equilibrium concepts have robust theoretical support and have been shown to explain behavioral patterns, there are no criteria to assess whether those notions hold in a specific setup. A different strand of the literature use the industry structure in solving for the equilibrium, such as the models of efficient entry (Berry, 1992, Quint and Einav, 2005) or those of selection by learning (Lee and Pakes, 2009, Wollmann, 2018). They usually apply in industries with a small number of firms, with a clear industry leader. However, the higher education market is highly segmented, with a large number of players and tight capacity constraints, therefore being an environment less compatible to this framework. I contribute by introducing an equilibrium concept that nests a criterion selection based on market data to select the degree of (bounded) rationality of players and that flexibly adapts to the industry structure.[3]

Overview The remainder of this paper is structured as follows. Section 2 gives details of the higher education market in Chile and the policy under study. Section 3 provides causal evidence of the policy impact. Section 4 presents the equilibrium model of the higher education market. Section 5 discusses the identification of the model and the estimation strategy. Section 6 shows the estimation results. Section 7 presents the counterfactual simulations. Section 8 concludes.

[3]Models of bounded rationality have been widely used in many fields, such as macroeconomics (Sargent, 1993), finance (Barberis & Thaler, 2002) and market design (Crawford & Iriberri, 2007). In the industrial organization literature, bounded rationality has generally been modelled for the consumer side (Heidhues & Kőszegi, 2018). Models where players perform simple heuristics or may hold mistaken beliefs include Osborne and Rubinstein (1998) and Camerer et al. (2004).

2 Setting

In this section I provide a description of my empirical application. Section 2.1 describes the market structure of the Chilean higher education system, section 2.2 describes the policy and provides some evidence of its effects, section 2.3 describes the data sources and descriptive statistics on the estimating sample, and 2.4 shows descriptive evidence on the relationship between pre-college achievement, as measured by the results of the university entrance exam, and teacher outcomes.

2.1 Higher Education Market

The higher education market in Chile is composed of 156 institutions, of 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 of 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 rank 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 test score requirement on a degree-by-degree basis.

In the period under study, the main funding options were two scholarships called *Beca Bicentenario* and *Beca Juan Gómez Millas*, which covered approximately 80% of tuition for students in the first two quintiles of the income distribution and who scored above 550 points in the PSU (an average of the Mathematics and Language component).[4] The other most common instrument to finance higher education were college loans, notably

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

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.

2.2 Teacher College Scholarship

During the 2000s, Education was the most popular degree of the Chilean higher education system[5]. Shortage of teachers was, therefore, not a concern. In fact, while 7-8 thousand students graduated from a Teacher College in a given year, only 4-6 thousand entered the labor market upon graduation. However, the performance of students who enrolled in Education degrees was substantially below those of other fields. Figure 1 shows the distribution of test scores of students enrolled in (i) teaching programs, (ii) any program and (iii) stem programs. Students in teaching programs scored below the universe of students pursuing a university degree, while the difference is wider compared to high-scoring fields such as STEM. Low salaries are likely to play a part, since teachers earn around 80% of the wage in professions with similar qualifications.[6] Additionally, 30% of all students entering an Education program do so without submitting scores of the University Entrance Exam.

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.[7] Eligible candidates must have scored an average above 600 points in the Language and Mathematics components of the university entrance exam (which corresponds to the top 20% of scorers).[8] 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.[9] The policy 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 require-

[5]Table A3 shows that in 2010, the year before implementation, the market share of Education degrees was 14%, the third after Technology and Health. However, no individual degree from within those fields had a higher market share.

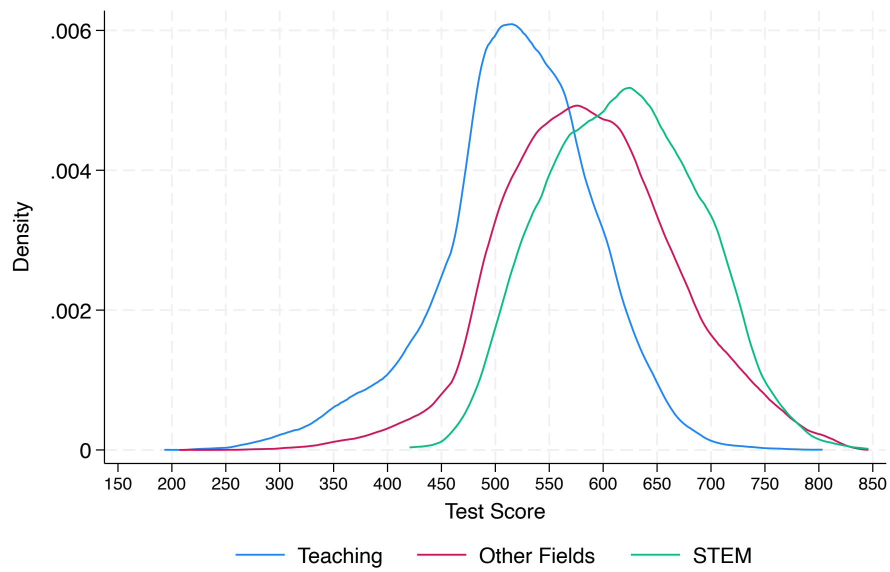
[6]UIS-UNESCO, 2020.

[7]The policy also has as beneficiaries individuals who hold of a Bachelors degree (or in their last year of studies) and want to take a pedagogical complement (2 years long) to become teachers. However, I don't include them in the analysis, since they represent a negligible fraction of beneficiaries.

[8]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. I don't consider this threshold in my analysis since that less than 5% of beneficiaries belong to this group.

[9]In practice, less than 2% of scholarship holders qualified through this channel

Figure 1: Test score distribution, by field of study



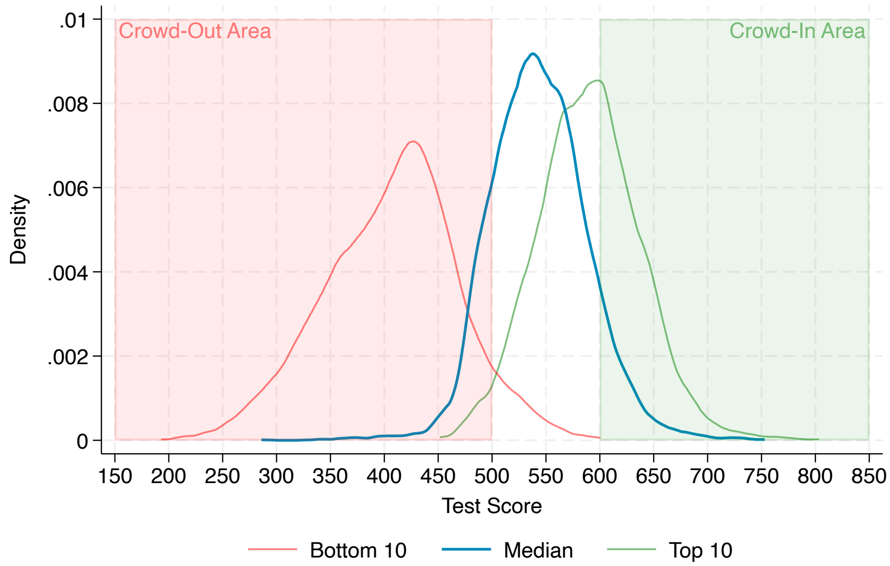
NOTES: This figure shows the distribution of test scores for students enrolled in teacher programs, students enrolled in other fields, and students enrolled in a STEM degree, respectively, in 2010, the year before implementation of the teacher recruitment policy.

ment, that is, even students from SES-advanced backgrounds are eligible.[10]

The policy was established in public universities, while private colleges were given the option to participate. A condition was imposed to participating teacher colleges: if they wanted their students to benefit from the scholarship, they had to restrict enrollment of students who scored below the exam mean (500 points). For the most elite universities, this requirement was not binding as the cutoff score for teaching degrees was above this floor. However, for many universities this requirement implied a sizable reduction in enrollment, so they decided to opt out of the program. Figure 2 shows the distribution of test scores for different groups of teacher colleges in 2010 (the year before implementation). While for the top teacher colleges the floor would not have impacted their enrollment (their cutoffs were already above this floor), those colleges with the lowest scoring students had virtually all of their enrollment below the 500 floor. For the Median college, it wasn't straightforward to assume which decision will lead to higher revenues. Table A1 shows that 53% of Education programs participated in the policy upon implementation, reaching 57% by 2015. However, participation within private colleges was 30%.

[10]Another condition for receiving the scholarship is that, upon graduation, beneficiaries have to work on a public-financed educational establishment for 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 (Bonomelli, 2017).

Figure 2: Test score distribution, teaching degrees



NOTES: This figure shows the distribution of test scores for the bottom 10 teaching programs, the median program and the top 10 programs, respectively, in the year before the policy was implemented. The ranking is based on the average test score of enrolled students.

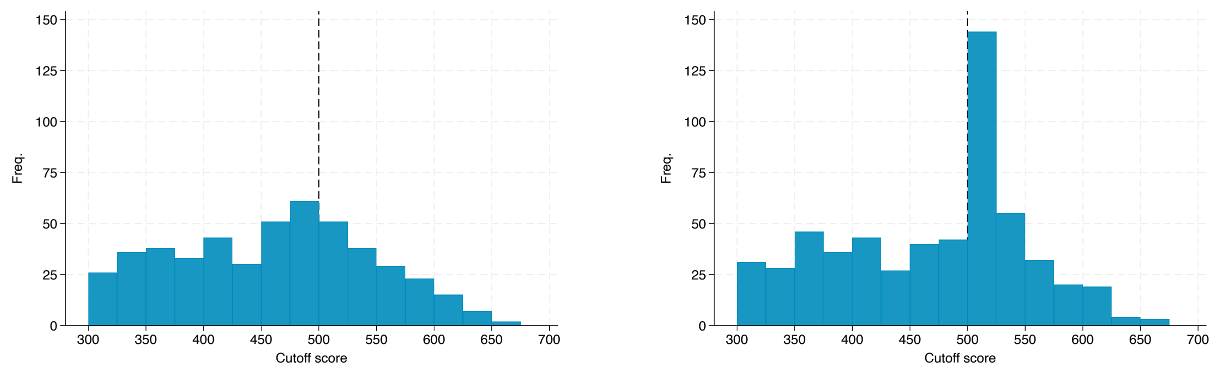
The introduction of the policy implied a shift in the minimum admission score of Education programs. Figures 3a and 3b show the histogram of cutoff scores in teaching degrees in 2010 and 2011, respectively. In 2010, a high share of programs located within the 450-500 points segment, but in 2011 there was a shift towards the 500-550 segment, related to the adherence of programs to the policy. However, there still was a considerable part of the distribution below the 500 points cutoff, composed of degrees that opted out.

2.3 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 organism of the University of Chile provided data on test score 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 estimating sample consist on every student who took the university entrance exam for the years 2009 to 2015, since the introduction of Free College in 2016 made the scholarship less attractive and negatively impacted the pool of students self-selecting into

Figure 3: Cutoff score at teaching programs

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



NOTES: These figures show the histograms for enrollment at teaching programs in 2010 (Figure 3a) and 2011 (Figure 3b). A program is defined at the Institution-degree-campus level, and it includes every higher education institution.

teaching degrees (Castro-Zarzur et al., 2022).

Administrative records for the universe of teachers was provided by MINEDUC. The data includes information on teacher college, degree, and graduation year, as well as demographic characteristics. Teachers share a unique identifier with the students' data, which allows me to link students to their later teaching careers. Teachers can also be linked at the school-grade-class level, which allows me to compute teacher value added measures.

The Ministry also provided the results from the Teacher Evaluation Program, known as *Evaluación Docente*, which is a comprehensive framework established to assess the professional performance of teachers working in municipal schools throughout Chile. Teachers are classified into four performance categories: Outstanding, Competent, Basic, and Unsatisfactory. These categories have direct implications for career advancement, salary incentives, and access to professional development opportunities. Teachers rated as Outstanding or Competent may receive recognition and financial bonuses, while those rated as Basic or Unsatisfactory are required to participate in targeted professional development and may undergo more frequent evaluations. Notable, if a teacher scores Unsatisfactory in three ocations, he must leave the school and is not allowed to teach anymore.

The evaluation process is multifaceted and involves (i) Self-Evaluation: Teachers complete a self-assessment, reflecting on their strengths, areas for improvement, and professional goals, (ii) Peer Evaluation: Trained peer evaluators, typically experienced teachers, observe classroom practices and provide feedback based on standardized criteria, (iii)

Principal's Report: School principals or direct supervisors contribute an assessment based on their observations of the teacher's performance, professional conduct, and contribution to the school community, and (iv) Portfolio: Teachers prepare a portfolio that includes lesson plans, classroom materials, and evidence of student learning. This component has the higher weight of the evaluation (60%) and is divided into two modules: in the first, teachers submit a detailed lesson plan, supporting teaching materials, and answer a questionnaire on teaching practices. In the second module, teachers record and submit a video of an actual class session, showcasing their instructional strategies, classroom management, and interaction with students. The portfolio component was designed to directly measure teaching skills, and is the one I use as an outcome in my analysis.

Tables A2 and A3 show descriptive statistics for degrees and test takers, respectively. From every bachelor-granting institution, close to a half operated 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, while students from higher socioeconomic status had a greater representation in 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 were 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.

2.4 Descriptive Evidence

In addition to the portfolio component of the Teacher Evaluation Program, I measure teacher effectiveness by estimating Teacher Value Added (TVA), which I compute (following Bacher-Hicks and Koedel, 2023) from the equation:[11]

[11] There's a large literature on the estimation of Teacher Value Added. Recent contributions include Chetty et al. (2014b), Araujo et al. (2016) and Bau and Das (2020).

$$y_{igjst} = \sum_a \beta_a y_{i,t-1} I_{it}(\text{grade} = a) + \tau_g + \rho_j + \omega_s + \chi_t + \upsilon_{isjgt} \tag{1}$$

where an outcome for student i in school s, who received instruction by teacher j in grade 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[12]. Because of data availability,[13] I compute mathematics teacher value added measures for 6th and 8th grade teachers, from 2013 to 2017.

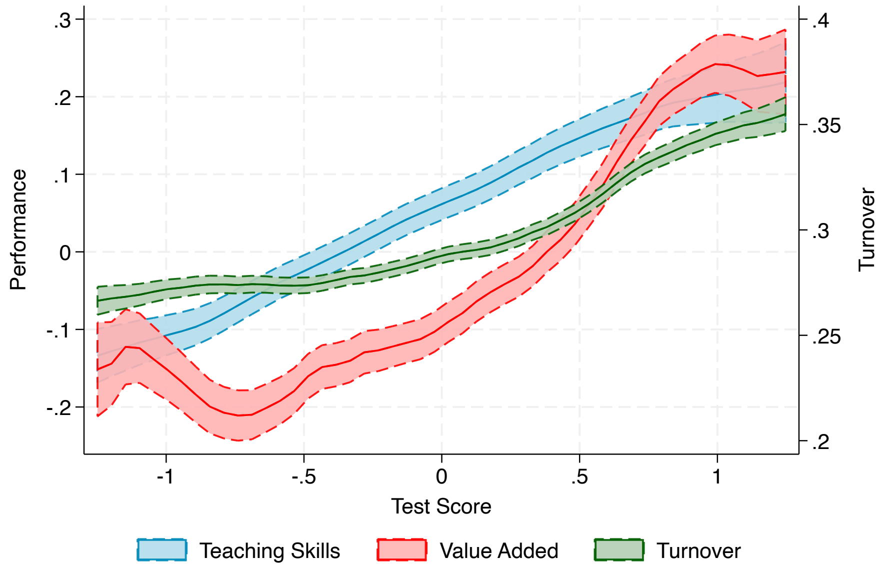
Figure 4 shows the relationship between test scores at the University Entrance Exam and the two outcomes of teacher effectiveness under consideration. It can be seen that teachers who scored a higher score tend to perform better, as measured by their Teaching Skills and their Value Added. A simple regression yields that a 1SD increase in test scores is associated with a 0.18SD increase in Teaching Skills and 0.21SD increase in Value Added. This gives scope for a policy based on pre-college achievement to improve recruitment, which is explored in the following section.

The Figure also shows the relationship between test scores and the probability of leaving the profession within the first five years, which is also positive. In this case, a simple regression yields that a 1SD increase in test scores is associated with a 3 percentage point increase in the probability of leaving the profession, which is consistent with the idea that higher performing students are more likely to find better job opportunities outside teaching.

[12]This specification does not allow for the existence of teacher-student match-effects, which has been recently featured in the literature (Ahn et al., 2024, Bates et al., 2025, Bobba et al., 2024). However, as I don't explicitly model the sorting of teachers into schools, I cannot identify these effects under counterfactual assignments.

[13]Standardized tests (SIMCE) were given from 2011 to 2018 to 4th grade students, from 2013 to 2015 to 6th grade students and in 2013, 2014, 2015, 2017 and 2019 for 8th grade students. In order to control for prior achievement, I estimate Value Added for 6th grade teachers in 2013, 2014 and 2015, and 8th grade teachers in 2015 and 2017.

Figure 4: Test Scores and Teacher Outcomes



NOTES: This figure shows the relationship between test scores at the University Entrance Exam, the two measures of teacher effectiveness (Teaching Skills and Value Added) and Turnover within the first five years in the profession, by performing a kernel-weighted local polynomial smoothing. The shaded area corresponds to the 95% confidence intervals. The left vertical axis corresponds to the standardized value of the performance measures, while the right vertical axis corresponds to mean turnover. Outcomes and test scores are standardized to have mean zero and standard deviation one.

3 Policy Effects

This section provides empirical evidence on the effects of the policy. Section 3.1 investigates whether the program was effective in attracting high-achieving students to the teaching profession using a regression discontinuity (RD) approach. Section 3.2 examines the policy's impact on labor market outcomes—specifically, whether these higher-achieving students go on to perform better as teachers—through a Differences-in-Differences (DID) analysis. Finally, Section 3.3 explores other potential impacts of the policy, including the effect on Turnover and on the placement of teachers in private schools.

3.1 Enrollment Effects

I exploit the discontinuities in program eligibility around the performance floor (500 points) and the scholarship eligibility threshold (600 points), and thus I compare students who scored just below and just above these cutoffs. I estimate the following equation:

$$EnrolledTeaching_i = \alpha_0 + \alpha_1 \cdot \mathbb{1}(s_i \geq e) + f(s_i - e) + \alpha_2 X_i + \epsilon_i \tag{2}$$

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. For the scholarship threshold, it identifies the effect of program eligibility on teacher degree enrollment. Take-up of the scholarship is above 90% for students who score above the threshold (high-performing students also enroll in non-participating degrees), and the estimate is interpreted as an intention-to-treat effect. For the performance floor, it identifies the substitution patterns due to the exogenous variation in feasible choice sets.

A number of confounding issues may arise with this strategy. First, I check the correct implementation of the program by testing if scoring above the cutoff implies a change 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 B1a 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. This condition, therefore, might have discouraged students of enrolling in a teaching degree but, conditional on enrollment, it didn't dissuade them of taking the scholarship.

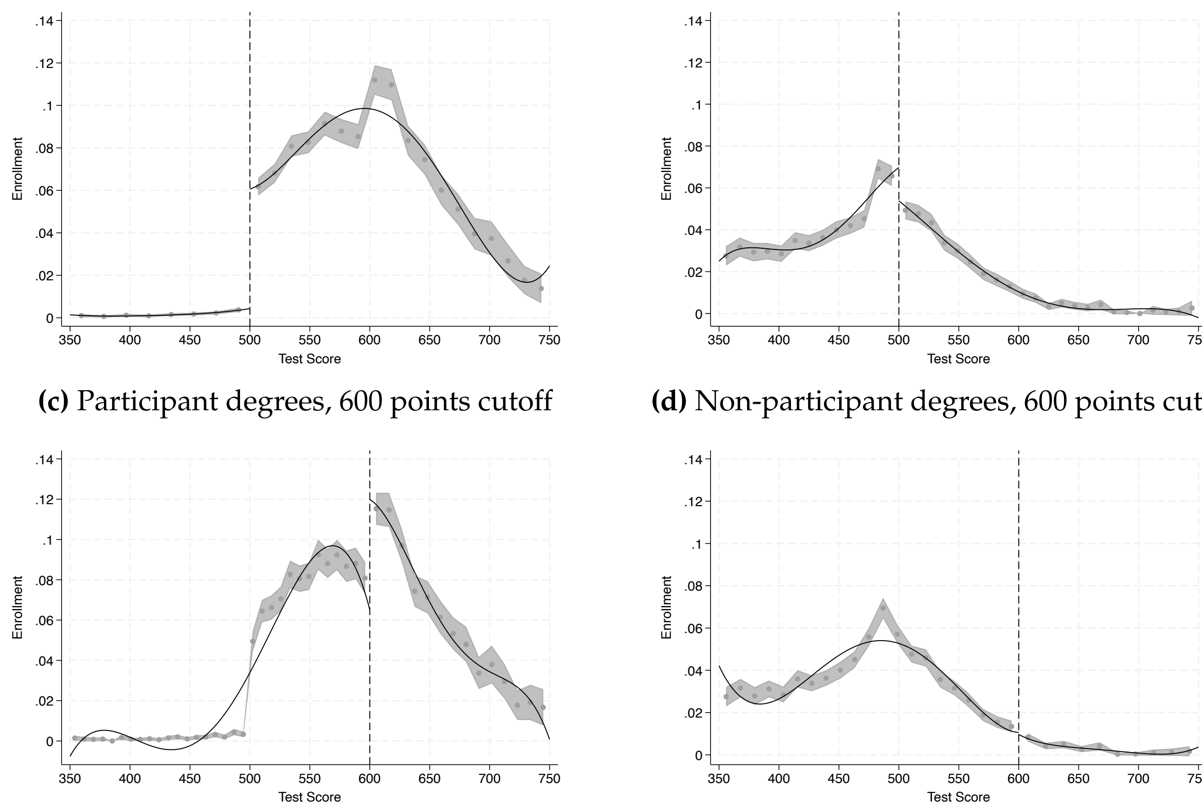
With respect to manipulation of the running variable, I perform the manipulation test of Cattaneo et al. (2020). Figure B1b shows the results of the no discontinuity around the cutoff (p.value = .829), evidencing that students couldn't influence their final score (besides from exerting effort). In the 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 enrollment results 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 B9. The estimates show no significant effect on retaking behavior.

Table B7 shows the result of estimating Equation 2 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.

In Figure 5, I plot the mean enrollment at teacher colleges within bins of test scores, with a 4th degree polynomial fit on different sides of the thresholds (following Calonico et al., 2015). Figures 5a and 5b 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 5c and 5d do the same for the 600 points threshold. Figure 5a shows that, for people that scored below 500, mean enrollment is zero, which constitutes evidence of the correct implementation of the policy. For non-participant degrees, Figure 5b shows that 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 relate this magnitude to 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. However, 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.

With respect to scholarship eligibility, Figure 5c shows that, 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. Finally, there are no discontinuities at the 600 points, something expected given that scoring above that threshold give no benefit at non-participating degrees. It also reveals that, at the scholarship eligibility threshold, there is no substitution from non-participating to participating teaching degrees.

Figure 5: 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 5a and 5b, a 4th degree polynomial is fit on each side of the 500 points cutoff, while in 5c and 5d the same is done for the 600 points cutoff. Every plot is obtained using the 2011 data.

Table 1 shows the results of estimating equation 2 on the different thresholds, by fitting a local linear regression on each side of the threshold (following Calonico et al., 2015). 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 percentage points in enrollment. Considering that mean enrollment below the cutoff is 8.7%, it represents a 42% increase in the probability of enrolling at a teacher college. In Tables B1-B6 of the appendix I show that the results in Table 1 are robust to different estimation specifications, such as covariate controls, the bandwidth chosen and the specification of $f(.)$. Column 3 shows that, at the 500 points threshold, the probability of enrolling in a Non-Participant teaching degree decreases 1.8 percentage points, which relates to student substituting into Participant degrees. Column 4 shows the null effect at the 600 points threshold for Non-Participant degrees, as was the case for Figure 5d.

Table 1: Estimates of enrollment at teaching degrees

	Participant		Non-Participant	
	(1)	(2)	(3)	(4)
Enrollment	0.052***	0.037***	-0.018***	-0.003
	(0.003)	(0.006)	(0.003)	(0.002)
Cutoff	500	600	500	600
Observations	78258	42932	105408	41872
Bandwidth	44.1	36.5	61.4	35.9
Baseline	.004	.086	.067	.014

NOTES: This table shows the estimates from the RD design. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

I also perform four placebo tests on the results found in Table 1. Results are shown in Table B8. 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 500 and 600 point thresholds in year 2010, before the program was implemented. As expected, I don't find an effect in none of the cases.

This result 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 B10. 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).

Having shown the increase in enrollment at teaching degrees around the scholarship cutoff. Table 2 shows the RD estimates for different groups of degrees, plus an option for not enrolling. Panel A estimates the effect for Low Income students, defined as those with a family income below the median, while Panel B shows the results for High Income students. Results show that the intention-to-treat effect is twice as large for Low Income students (5.1 versus 2.6 percentage points). In terms of the relative increase, however, the effect is similar for both groups, because High Income students have a lower baseline probability of enrolling in a teaching degree at the 600 points threshold.

Table 2: Estimates of enrollment by income at the 600 points cutoff

Dep. Var: *Enrollment*	(1) Estimate	(2) SE	(3) Observations	(4) Bandwidth	(5) Baseline
Panel A: Low Income					
Education (Participant)	0.051***	(0.009)	28374	43.4	.108
Education (Non-Participant)	–0.001	(0.002)	36514	55.4	.015
Other Bachelor	–0.020	(0.013)	28374	43.5	.568
Short Cycle Program	0.007	(0.007)	29578	45.1	.084
Not Enrolled	–0.032***	(0.010)	29038	44	.197
Panel B: High Income					
Education (Participant)	0.026***	(0.007)	23281	45.3	.057
Education (Non-Participant)	–0.004	(0.003)	26111	51.2	.013
Other Bachelor	–0.026*	(0.015)	18661	35.9	.614
Short Cycle Program	0.004	(0.007)	23061	44.8	.069
Not Enrolled	0.015	(0.013)	16351	31.3	.201

NOTES: This table shows the estimates from the RD design. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2 shows that there is also heterogeneity by family income on the substitution patterns. For Low-Income students, two-thirds of the increased enrollment at Teaching Degrees comes from students who have Non-enrollment as their next-best alternative, while the rest is explained by students coming out from other Bachelor programs. For High Income students, the increase is entirely explained by students substituting away from other Bachelor program. Table B11 shows the results for the 500 point threshold. The substitution effect is similar for both groups of students. However, close to a third of the substitution derives from students who have a Short Cycle Program as their next-best alternative, while for High Income students all the remaining substitution is derived from Non-enrollment.

Three lessons can be drawn from these results: first, the bigger intention-to-treat effect reveals a higher price sensitivity for Low Income students. Second, the higher baseline enrollment share for Low Income students suggests that they have a higher preference for teaching degrees. Third, the different substitution patterns imply that competitive pressure to other degrees comes mostly from High-Income students. These results suggest that an alternative policy, targeted to Low Income students, could prove to be more effective, and motivates the decisions to simulate a Means-based policy in Section 7.

3.2 Performance 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 between being a good student (in terms of test scores) and a good teacher is not straightforward (Jackson et al., 2014). I study the impact that the policy had on teacher quality by performing a Differences-in-Difference (DID) analysis. In particular, I estimate the following equation:

$$Y_{ijt} = \beta_1 \text{ParticipantDegree}_i + \beta_2 \text{ParticipantDegree}_i \times \text{Post}_t + X_i' \beta_x + \mu_t + \epsilon_{ijt} \quad (3)$$

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 policy-participant degree (all teaching degrees from public universities, plus the ones from private colleges that opted-in) and 0 if not. The post dummy stands for post 2011 cohorts, X_i includes sociodemographic characteristics and μ_t are year fixed effects.

Equation 3 compares outcomes from teachers who enrolled in Participating and Non-Participating Programs, for cohorts before and after the policy was implemented. The identifying assumption is that the only difference for Participating programs before and after the policy is the improved pool of students enrolled, and assumes that other factors such as college quality (the contribution of a college to teacher effectiveness) remained constant over time. I test this hypothesis by estimating Equation 3 in two ways: first, without controlling for any observable characteristic, and then by including as covariates measures of pre-college achievement. Intuitively, if the only difference is due to compositional changes, the post-policy differences should disappear after controlling for these characteristics.

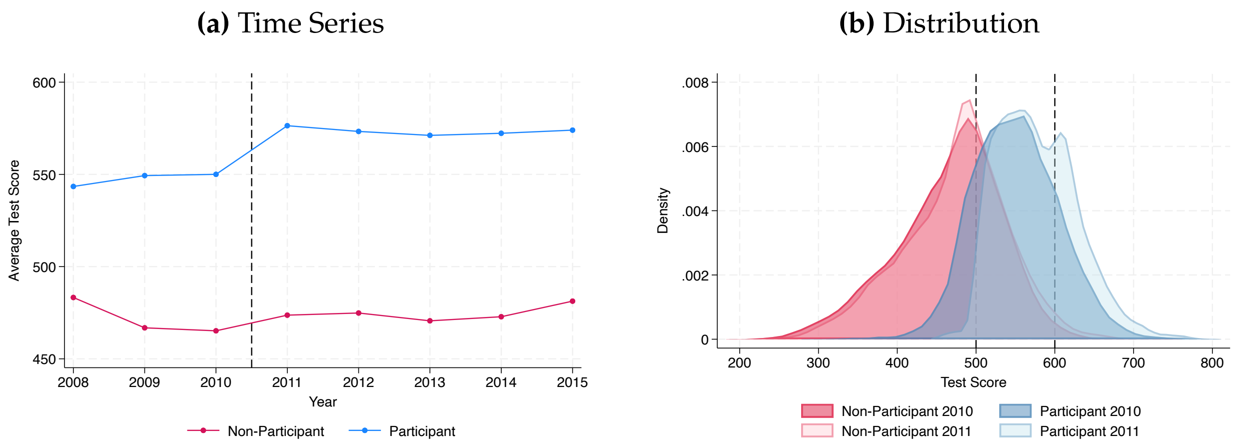
There exist several threats to identification. One is due to the endogenous decision of universities to participate in the policy on a degree-by-degree basis. However, the participation decision is fixed by the time the students make their enrollment decisions. Therefore, the decision process by universities 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 participating and not participating degrees that could explain the expanding gap post policy. Figure 6a shows the trends for test scores for Participating and Non-Participating degrees. While they remained mostly constant before the policy, there's an increase in average test scores in participating universities after implementation, while it remains mostly constant for students in Non-Participating degrees. Figure C1 studies the existence of pre-trends for Test Scores and teacher effectiveness measures by means of an event study design, and results point against the existence of pre-trends.

Lastly, a third threat could be due to transition between groups which implies a SUTVA (Stable Unit Treatment Value Assignment) violation. Indeed, while Column 4 of Table 1 shows no negative impact for Non-Participating degrees at the 600 points threshold, Columns 1 and 3 reveal that some students who were crowded out at the 500 points threshold enroll in Non-Participating degrees.

I argue that the policy implied a positive spillover to Non-Participating degrees: the influx of higher performing students 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. Two additional pieces of evidence supports this theory: first, Figure 6a shows that average test scores in Non-Participating degrees were close to 460 points, and the average raises slightly after the policy. Second, Figure 6b plots the distribution of test scores for Participant and Non-Participant degrees, both in 2010 (the year prior to the introduction of the policy) and 2011 (the year of implementation). For Participant degrees, a two-fold shift can be seen in the distribution: at 500 points due to the performance floor, and at 600 points due to the scholarship. For Non-Participant degrees, the right tail remains roughly constant. However, there is variation at the 500 points area, where students are crowded out of Participating degrees and substitute into the Non-Participant. These are above-average students, and the left tail of the distribution shifts to the right.

Figure 6: Test Score



NOTES: These figures shows statistics on the average between the mathematics and language components of the University Entrance Exam. Figure 6a plots the evolution in time for test scores in Participating and Non-Participating degrees, while Figure 6b plots the distribution of test scores for Participating and Non-Participating degrees, for 2010 (the year before implementation) and 2011 (the year the policy was implemented).

To measure the composition effect, I estimate Equation 3 with the average of the language and mathematics component of the University Entrance Exam as the outcome variable, for primary school teachers in the period 2011-2019 which belong to the 2006-2014 cohorts. I use two measures of teacher effectiveness. The first one is teacher value added, as estimated by Equation 1. I restrict the subsample to teachers from the 2008-2012 cohorts (from one year pre-policy until two years post-policy).[14]

The second measure of effectiveness comes from the Teacher Evaluations Program performed by the Chilean Ministry of Education. Details are provided in section 2.3. I consider as outcome the Portfolio component of the evaluation, which was specifically designed to measure teaching skills. For this outcome, the estimating sample are primary school teachers in public schools for cohorts 2006 to 2014. Test Scores, Value Added and Teaching Skills measures were normalized to have mean 0 and standard deviation 1, so estimates are interpreted in SD sizes.

Table 3 shows the result of the DID estimation. Column 1 shows that teachers that graduated from Participating degrees had on average 0.42SD higher Test Scores. However, after the policy the gap further expanded another 0.25SD. Columns 2 to 5 show the results for

[14]The 2012 cohort is the last one that can be observed teaching by 2017.

Teaching Skills and Value Added, respectively. Columns 2 and 4 show that the difference between the groups, in terms of their teaching effectiveness, was of 0.16SD and 0.12SD. This was something expected, as the most prestigious universities are the ones who participated. However, after the policy the difference increases by an additional 0.12SD for Teaching Skills and 0.11SD for Value Added. Column 3 and 5 shows that, when controlling for Test Scores, teachers were on average 0.09SD better in terms of Teaching Skills and 0.06SD in terms of Value Added, which suggests that teachers that graduate from Participating degrees are not only better because they were better students, but also because they were trained in a better environment. Notably, when controlling for Test Scores, the post-policy difference disappears: for Teaching Skills, the point estimate is not statistically different from 0, while for Value Added the point estimate is effectively zero. These results confirm the hypothesis of pure-composition effect.

Table 3: Estimates of Teacher Performance

	Test Score	Teaching Skills		Value Added	
	(1)	(2)	(3)	(4)	(5)
ParticipantCollege	0.42^{***}	0.16^{***}	0.09^{***}	0.12^{***}	0.06^{**}
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)
Post=1 $\times$ ParticipantCollege=1	0.25^{***}	0.12^{***}	0.06	0.11^{***}	-0.00
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)
Test Score			0.14^{***}		0.09^{***}
			(0.01)		(0.01)
Observations	19398	9628	9628	1774	1774

NOTES: This table shows the estimates from the Difference-in-Differences regression on labor market outcomes. In column (1) the sample is composed of primary school teachers from cohorts 2006-2014. In column (2) and (3), the sample includes every primary school teacher from cohorts 2006-2014. In columns (4) and (5), the sample includes 6th and 8th grade teachers for 2008-2012 cohorts. In all cases, robust standard errors are computed.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.3 Other Effects

In this section, I estimate if the policy had an effect on teacher turnover. As explained in Section 2.2, beneficiaries of the scholarship are required to teach at publicly-funded schools for three years within seven years of graduation. Besides the substitution between institutions, this requirement could have induced retention of teachers, as they would be less likely to leave the profession before fulfilling their obligation. I estimate Equation 2 on the probability of leaving the profession within the first five years, and on the probability of teaching at a private school within the first five years. Table 4 shows that the estimates yield a precise null effect, which suggests that the scholarship did not have an effect on turnover, nor the type of institution.

The policy could have nevertheless had an effect on turnover, due to the compositional changes in the pool of students enrolled at teacher colleges. I estimate Equation 3 with those two outcomes in mind. Table 5 shows the estimates, which also indicate that the policy did not have an effect on turnover, nor on the type of institution where teachers were placed.

Table 4: Estimates of Turnover (RD)

	(1) Private School	(2) Exit
Estimate	-0.002	-0.007
	(0.016)	(0.018)
Cutoff	600	600
Observations	4342	5457
Bandwidth	44	56.8
Baseline	.055	.104

NOTES: This table shows the estimates from the RD design. In the first column, the dependent variable takes value 1 if a Teacher is observed on a private school within the first 5 years of teaching. In the second column, the dependent variable takes value 1 if a Teacher exits the profession within the first 5 years of teaching. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Estimates of Turnover (DID)

	(1) Private School	(2) Turnover
ParticipantCollege	0.01^{***}	0.00
	(0.00)	(0.01)
Post=1 $\times$ ParticipantCollege=1	-0.01^{*}	-0.01
	(0.00)	(0.01)
Observations	19398	19398

NOTES: This table shows the estimates from the Difference-in-Differences regression on labor market outcomes. The sample is composed of primary school teachers from cohorts 2006-2014. In column (1), the dependent variable takes value 1 if a teacher is observed in a private school within the first 5 years of teaching. In column (2), the dependent variable takes value 1 if a teacher exits the profession within the first 5 years of teaching. In all cases, robust standard errors are computed.
*** p $<$ 0.01, ** p$<$ 0.05, * p$<$0.1

4 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. Also, the identification strategy for teacher quality (DID) does not allow me to decompose the relative contribution of each policy rule. Finally, my ultimate goal is to determine the optimal policy design, for which I need to simulate the market equilibrium under alternative policy rules. For these reasons, I build an equilibrium model of the higher education market, 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.

4.1 Environment

The higher education market is characterized by a set $\mathcal{I}$ of individuals (students) such that $i \in \mathcal{I} = \{1, ..., n\}$, and a set $\mathcal{J}$ of college degree programs such that $j \in \mathcal{J} = \{1, ..., J\}$, with $j = 0$ as the outside option (not enrolling in any program). In each period $t \in T$, the government announces a set P of educational policies for every degree, based on individual characteristics z_i and degree characteristics x_j, both observed by the policy-maker.

These policies relate to incentives (such as grants or scholarships) and selectivity (such as performance floors). In my application, P includes every ongoing policy, including the Teacher Recruitment Policy, to which private universities make the strategic decision of participation.

The Chilean Higher Education Market is dual, with a subset of colleges participating in the Centralized Admission System,[15] while the rest enroll students in a decentralized way. I consider the Centralized portion of the market and the off-platform Education programs.[16] 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.[17] 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 v_j specifies the vacancies for degree j, and $v_0 = \infty$. In determining enrollment, a student is characterized by his preference order and score, i.e. $\psi_i = (\succ_i, s_i)$.

Within each period $t = \{1, ..., T\}$, the timing is as follows:

1. The government announces educational policies P for every higher education degree.
2. Colleges observe P and:
   (a) If they offer an Education degree, they decide on policy participation.
   (b) They set tuition for every degree.
3. Students observe P and the listed degrees and submit ranked ordered lists.
4. The centralized system matches students to degrees.

The centralized admission process implements a college-proposing version of the deferred acceptance algorithm. I define the mechanism $\phi(\psi, v) = \mu$, where μ is the realized matching, given students' types and colleges' vacancies per degree. The algorithm ensures that each student is assigned his most preferred degree among the available ones

[15]I model the Centralized part of the market closely following the literature (Azevedo and Leshno, 2016, Abdulkadiroğlu et al., 2017)

[16]In 2011 there were 1020 programs listed on the platform. I include the Education programs that are offered by 19 universities outside the platform. Results are robust to an alternative environment in which the off-platform market is explicitly modelled, as in Kapor et al. (2024).

[17]In practice, programs always consider the mathematics and language components of the University Entrance Exam, and they can optionally put weight to the social sciences, natural sciences or other optional exams, and their high school GPA.

(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[18]. 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 $D_i(\mu) = \mu(\psi_i)$.

4.2 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.[19] A student i's indirect utility for attending program j is given by:[20]

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

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:

$$\begin{aligned} u_{ij} &= V_{ij} + \eta_{ij} \\ &= \delta_j + \alpha_p op_{ij} + \alpha_w w_{ij} + \alpha_z z_i + \alpha_q x_j z_i + \eta_{ij} \end{aligned} \tag{5}$$

The parameter δ_j includes time-invariant program characteristics (both observed and unobserved). 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 η_{ij} is assumed to follow a type-1 extreme value distribution.

In my empirical application, z_i includes a constant, the math-language average test score,

[18] 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).

[19] While flexible enough, this framework does not account for all possible factors influencing student choices, notably characteristics of their peers. As an equilibrium object, endogenous peer composition has been challenging to incorporate for the higher education market. For elementary education, recent contributions can be found in Ferreyra and Kosenok (2018) and Allende (2019).

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

the mother's education level and an indicator variable for coming from a private high school. Match characteristics w_{ij} includes a dummy which takes value 1 if the student lives in a different region than the program and the monetary value of the scholarship he's eligible to if enrolling in that program. College characteristics x_j include a program's field and college group[21]. Individual characteristics z_i are interacted with both program characteristics and match characteristics. 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.[22] I estimate the model separately for Low and High Income students, where a student is defined as Low Income if his family income is below the median, and High Income otherwise.

The probability that student i chooses degree j can be written as:

$$s_{ij} = \frac{\exp V_{ijt}}{\sum_{k \in \Omega_i} \exp V_{ikt}} \tag{6}$$

where the feasible choice set Ω_i includes every degree with a cutoff below the student's program-specific score.

4.3 Supply

Colleges compete in a static Bertrand differentiated product framework by setting tuition p_j for all their offered degrees.[23] Additionally, private universities make the (joint) discrete decision $B_j \in \{0, 1\}$ for their Education degree, which determines participation in the Teacher Recruitment Policy.[24] Without loss of generality, $B_j = 0$ is fixed for non-Education program, and $B_j = 1$ is fixed for Education programs at public universities. Colleges are not allowed to price-discriminate, and the effective price paid by a student will depend solely on his scholarship status. In each period, the colleges' joint profit maximization problem is given by:

$$\max_{\{B_j, p_j\}_{j \in \mathcal{F}_f}} \sum_{j \in \mathcal{F}_f} (\Pi_j(p)) \tag{7}$$

[21] Colleges are divided into four groups, defined by their private/public status and their selectivity.
[22] Details of the estimation strategy can be found in Section 5.
[23] For ease of exposition, I suppress the time sub-index t in this section.
[24] While this framework is flexible enough to capture the key determinants of the market, it omits important features, such as endogenous degree offerings, entry/exit of universities, and the possibility to impact demand by investing in quality or advertisement.

$$\Pi_j(p) \equiv \sum_{k=0}^{1} \left(\mathbb{1}\{B_j = k\} \cdot \sum_{i \in \mathcal{I}} (s_{ij}(B, p_j, .) \cdot [p_j - c_j]) \right) \tag{8}$$

where $\mathcal{F}_f$ is the set of degrees offered by college f, $B_j \in \{0, 1\}$ is the policy participation decision, p_j the tuition for degree j, and c_j are the marginal costs. The choice probability 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 its 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:

$$op_{ij} = \begin{cases} p_j & \text{if } B_j = 0 \\ (1 - \lambda_{ij})p_j & \text{if } B_j = 1 \end{cases} \tag{9}$$

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[25], and they would risk losing enrollment from non-scholarship holders who would prefer to enroll in a different program. In addition, the policy caps price increases of participant degrees to the consumer price index.[26]

4.4 Outcomes

The goal of the potential outcomes model is to predict outcomes for students who didn't enroll in a teacher program, for the counterfactual scenario in which they study to become teachers. I will focus on two specific outcomes: Teacher Value Added and Turnover Propensity.[27][28] I assume the potential outcome for student i in program j has the follow-

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

[26]This price cap acts as a constraint on the colleges' pricing decisions. If this constraint is binding, marginal costs cannot be point identified, and only bounds can be estimated. In practice, I observe that only one participating program raised prices up to the cap, so in general the constraint wasn't binding. For counterfactuals, I fix the marginal cost of this program to the estimated value in the year before implementation of the policy.

[27]The decision to leave the profession at a given point is in practice the result of a complex set of factors. This approach seeks to capture the latent propensity that a given individual has in leaving the profession, which correlates to preferences and observable attributes.

[28]In practice, the outcome is a dummy variable which takes the value 1 if the individual leaves the profession within 5 years, and 0 otherwise.

ing functional form:

$$Y_{ij} = \mu_j + X_i\beta_j + \epsilon_{ij} \tag{10}$$

The expected outcome conditional on enrollment can be expressed as:

$$E[Y_{ij}|X_i, D_i = j] = \mu_j + X_i\beta_j + E[\epsilon_{ij}|X_i, D_i = j] \tag{11}$$

The assumption required for an OLS regression to yield unbiased estimates is that of "selection on observables": enrollment in a given program should be as good as random, conditional on covariates X_i. If students self-select into programs based on their potential outcomes, then $E[\epsilon_{ij}|X_i, D_i = j]$ is not equal to 0, and a simple OLS regression would yield biased estimates of the parameters. For the outcomes under consideration, selection on unobservables is likely the case, and should be taken into account.[29] I proceed to follow a control function approach that links potential outcomes to preferences[30] over degrees by conditioning potential outcomes on unobserved preferences over every degree inside a student's choice set. This approach implies the restriction:

$$E[Y_{ij}|X_i, D_i = j, \eta_i] = \mu_j + X_i\beta_j + g_j(\eta_i) \tag{12}$$

where η_i is a vector of size equal to Ω_i, and $g_j(\eta_i)$ a function that flexibly controls for a student's unobserved preferences and allows potential outcomes to vary according to them. Following the multinomial logit selection model of Dubin and McFadden (1984), I further parameterize the function $g_j(\eta_i)$ as a linear combination of the unobserved preferences:

$$E[Y_{ij}|X_i, D_i = j] = \mu_j + X_i\beta_j + \sum_{k\in\Omega_i} \omega_k\, \eta_{ik} + \varphi\, \eta_{ij} \tag{13}$$

The parameter ω_k relates the taste for program k to all potential outcomes, capturing the fact that outcomes can be higher for students who strongly prefer a particular program. For example, a student with a strong preference over an elite engineering program is more likely to be a high ability student (beyond what is captured in test scores), implying

[29] As pointed out by Abdulkadiroğlu et al. (2020), selection on observables might be more plausible for short-term outcomes such as test scores, for which lagged measures are usually available.

[30] This approach has recently been used in the education literature by Walters (2018), Abdulkadiroğlu et al. (2020) and in the higher education market, Otero et al. (2021).

that he will have a higher potential outcome even if enrolling in a different program. The parameter φ is an additional match effect, and captures the fact that students may self-select to a program where his gains are higher.

4.5 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 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, and Fack et al. (2019) show that the matching game is equivalent to a discrete choice model with personalized choice sets.

For the supply side, colleges make a continuous choice (price) for every program they offer, and a joint discrete choice (policy participation) for their Teaching degrees. The pricing equilibrium, given participation, is proven to be unique with multiproduct firms and logit demand (Nocke and Schutz, 2018). To reach a Nash equilibrium, colleges need to solve a complex problem, as they need to anticipate the price equilibrium in each of the 2^N counterfactual market structures (to compute profits) and make a decision such that they correctly predict other colleges' actions and no college can increase profits by switching its participation decision. In the setup under consideration there are 60 education programs, and computing 2^{60} market structures is computationally infeasible (both for players and the econometrician). Therefore, I depart from standard equilibrium theory and assume players' actions follow a simpler heuristic: they focus on their close rivals' best responses.

Definition 1 *An equilibrium in Close Rivals is a set of actions and beliefs for every player such that:*

- *Players choose the action that yields a higher profit, given their beliefs.*
- *They hold correct beliefs about the actions of their close rivals.*

In terms of equilibrium theory, players are mutually rational because they choose what's best for them given their beliefs. However, mutual consistency doesn't hold, as they may have mistaken beliefs about actions of distant competitors.

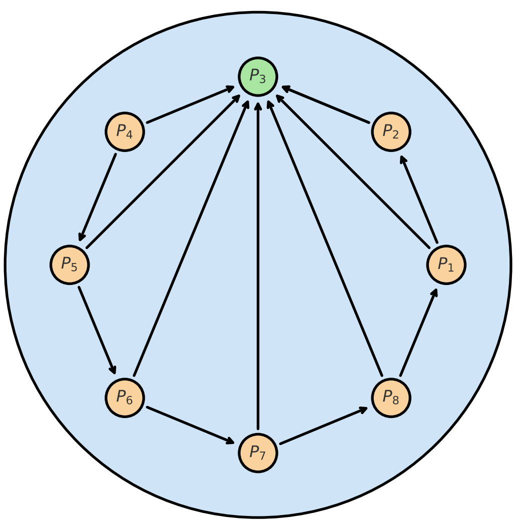
The notion of close rivals is defined by the cross-price elasticities of demand. The algorithm to choose the k closest rivals is as follows:

1. For each Education program j, compute $\partial s_j/\partial p_k$ for every Education program of another college.
2. Order the programs by $\partial s_j/\partial p_k$.
3. Select the k programs with the highest $\partial s_j/\partial p_k$.

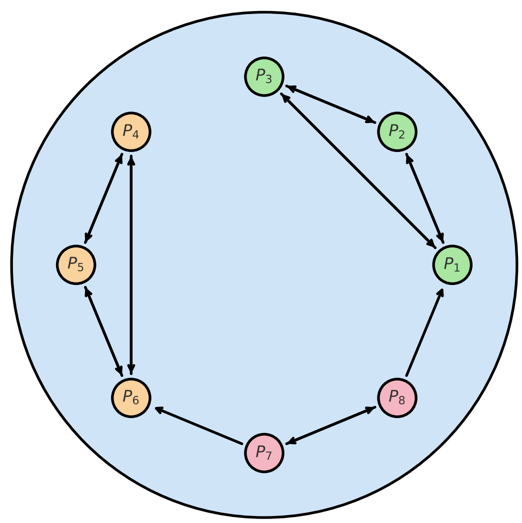
Therefore, the notion of being a "rival" includes only programs that participate in the discrete decision (policy participation), while every program is considered while making the continuous choice (prices). Note that rivality is not necessarily reciprocal: for players A and B, the fact that B is a close rival of A does not imply that A is a close rival of B. This notion, therefore, can accommodate different types of industries. Figure 7 shows the case of two close rivals in a concentrated industry (Subfigure 7a), where every player has an industry leader as a close rival, and a segmented industry (Subfigure 7b), where players tend to compete in clusters.

Figure 7: Equilibrium in Close Rivals

(a) Concentrated Industry



(b) Segmented Industry



NOTES: These figure shows examples of competition in different type of industries, for the case of 2 close rivals. Subfigure 7a shows a concentrated industry, where every player tracks an industry leader and a close rival. Subfigure 7b shows a segmented industry, where close rivals tend to form clusters.

The number of close rivals $k \in \{0, ..., N\}$ under consideration determines how sophisticated players are. If $n = 0$, then players completely ignore strategic responses. The limit case where $n = N$ coincides with a Nash Equilibrium.

4.6 Policy space

In the pursue of targeting students to certain degrees, the government can implement alternative educational policies, 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 Estimation

In this section, I discuss the identification of the model and the estimation strategy. Estimation is done sequentially. First, I recover the parameters of the demand model, which are the preference parameters $\alpha = (\alpha_p, \alpha_w, \alpha_z, \alpha_q)$ mean utilities δ_j for every program j. With these parameters, I can proceed to estimate the supply model and the potential outcomes model. On the former, I recover the marginal costs c_j of every program j by solving the first order condition of the profit maximization problem, as described in Equation 18. The estimates from the demand model also allow me to compute the unobserved preferences η_{ij} for every student-program pair, which are used to estimate the potential outcomes model. Finally, with the estimates from both the demand and supply model, I estimate the number of close rivals k that colleges consider when making their decisions.

5.1 Demand

I estimate the demand model following the method for differentiated products demand of Berry et al. (1995) enriched with the availability of data on individual attributes (Petrin, 2002, Berry et al., 2004), incorporating best practices (Conlon & Gortmaker, 2020; Conlon & Gortmaker, 2023). In particular, I observe the universe of test-takers of the University

Admission Exam, with their application portfolio, the matching generated by the platform, the actual program enrolled, and detailed information on sociodemographic characteristics, which allows me to flexibly control heterogeneity of preferences with respect to observable attributes. Different from them, I estimate individual choice probabilities and aggregate market shares with the matching generated by the centralized admission platform.

I estimate the preference parameters $\alpha = (\alpha_p, \alpha_w, \alpha_z, \alpha_q)$ and δ_j by minimizing the following log-likelihood function:

$$\mathcal{L}(\alpha, \delta) = \sum_{i=1}^{n} \sum_{j \in \Omega_i} \log \mathrm{P}\left(\mu_i^* \mid z_i, x_j, w_{ij}, \Omega_i \;;\; \alpha, \delta\right) \tag{14}$$

Where the probability of observing the matching μ_i^* depends on the characteristics of students and degrees, feasible choice sets and the parameters to estimate. The procedure, therefore, searches for the parameters that generate the students' rank ordered lists such that the estimated matching replicates the observed one.

The estimation embeds an inversion approach to recover mean utilities δ_j. For $\mathcal{J}$ products in the market, there is a unique vector of mean utilities $\delta_j(\alpha)$ that solves the system of $\mathcal{J}$ non-linear equations that equate the predicted market shares $s_j(\alpha, \delta)$ to the observed ones $\mathcal{S}_j$. The inversion is done by solving the following system of equations:

$$\mathcal{S}_j = s_j(\alpha, \delta_j(\alpha)) \quad \forall j \in \mathcal{J} \tag{15}$$

$$s_j(\alpha, \delta) \equiv \mathcal{I}^{-1} \sum_{\mathcal{I}} \mathbb{1}\{\mu_i(\alpha, \delta) = j\} \tag{16}$$

I use the nested fixed point algorithm of Berry et al. (1995). The inner loop, therefore, solves for the mean utilities δ_j that (for given α) make Equation 15 hold, while the outer loop minimizes the log-likelihood function in Equation 14, for a given vector of δ, by searching for the preference parameters α. The estimation is done separately for Low and High Income students.

In my model, prices p are equilibrium outcomes, and therefore a standard regression would yield biased estimates. I address the endogeneity 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-of-pocket tuition, and its associated price (dis)utility.[31] It can be shown that, if students are classified into types $l \in (1, ..., L)$ based on observable characteristics, the estimated price coefficient is a combination of the enrollment discontinuities at the threshold for each degree, weighted by the proportion of each student type and scaled by the degree's price:

$$\alpha_p = \frac{1}{L} \sum_{l=1}^{L} \left(\pi_l \frac{1}{J} \sum_{j \in \mathbb{J}} \frac{\lim_{r \to \bar{r}^+} \log \frac{s_{rlj}}{s_{rl0}} - \lim_{r \to \bar{r}^-} \log \frac{s_{rlj}}{s_{rl0}}}{p_j} \right) \tag{17}$$

with π_l as the share of students in type l and s_{rlj} as the market share for program j among students of type l with test score r. Appendix E provides the proof. In practice, estimation of the price coefficient (and its heterogeneity) is performed jointly with the rest of the parameters in the log-likelihood function, by including a third degree polynomial between a student's test score and an indicator if program j's field is Education. This flexible functional form allows me to capture the discontinuity in enrollment at the cutoff, while controlling for smooth changes in enrollment due to other factors. Appendix E provides further details on the identified parameter in a simplified model, and in Section 6.2 I show that the estimated parameters can succesfully replicate the discontinuities found in the data.

5.2 Supply

Optimal prices satisfy the colleges' first order conditions. Stacking up college f degrees, the following system of equations hold in equilibrium:

$$S^f + \Delta^f (P^f - C^f) = 0 \tag{18}$$

where $\Delta^f_{jk} = \frac{\partial s_k}{\partial p_j}$ for $j, k \in \mathcal{F}_f$, and S^f,P^f and C^f are the vectors of market shares, prices and marginal costs, respectively. Marginal costs are recovered by solving Equation 18 for the observed market shares and prices. They depend on the estimation of the demand parameters α (in order to compute the cross-price elasticities of demand Δ^f_{jk}), and therefore estimation is done sequentially.

[31] A similar strategy was used by Kapor et al. (2024) and Larroucau and Ríos (2024).

For the counterfactual exercises, the system of equations is solved for the equilibrium prices p given policy participation decisions B and marginal costs c.

5.3 Potential Outcomes

The parameters $(\mu, \beta, \omega, \varphi)$ of the outcome equation are recovered by estimating by OLS the following regression:

$$Y_i = \sum_{j \in \Omega_j} D_{ij}[\mu_j + X_i\beta_j] + \lambda_j(X_i, \Omega_i)[\omega_j + D_{ij}\varphi_j] + \epsilon_i \tag{19}$$

where D_{ij} is an indicator function that takes a value equal to one when students i enrolls in program j, and zero otherwise. The control function $\lambda_j(X_i, \Omega_i) = E[\eta_{ij}|X_i, \Omega_i, D_i = j]$ is the mean logit preference for program j, conditional on observable characteristics and the feasible choice set. These expressions have a closed-form solution and can be directly estimated from the data.

Estimates of program value added, while unbiased, are noisy estimates of the true parameters. In order to reduce the sampling variance, I perform an Empirical Bayes shrinkage, following Walters (2024).[32] Specifically, I assume the following model for the outcomes θ:

$$\hat{\theta}_i|\theta_i, s_i, z_i \sim \mathcal{N}(\theta_j, s_j^2) \tag{20}$$

$$\theta_i|s_i, z_i \sim \mathcal{N}(\gamma z_i, \sigma_r^2) \tag{21}$$

where σ_r^2 is the residual variance of θ_i (the fraction not explained by z_i). The posterior mean for θ_i is:

$$\theta^* = \frac{\sigma_r^2}{\sigma_r^2 + s_i^2}\hat{\theta}_i + \frac{s_i^2}{\sigma_r^2 + s_i^2}\gamma z_i \tag{22}$$

The estimator given by Equation 22 is the Empirical Bayes shrinkage estimator, which shrinks the noisy estimates towards the linear index $\hat{\gamma} z_i$. The shrinkage estimator is unbiased, and has been shown to exhibit significant lower Means Squared Error than the OLS counterpart. I estimate the hyperparameters γ and σ_r^2 via maximum likelihood.

[32] Gu and Koenker (2023) and Kline et al. (2024) highlight the importance of shrinkage for estimates involving ranking and selection.

One of the outcomes under consideration is Teacher Value Added, which is estimated on a previous step following Equation 1, with all teachers that had available information. When I plug the estimates in the left-hand side of Equation 19, I use the unshrunked estimates.

5.4 Equilibrium Selection

Close Rivals are determined by the estimated $\hat{\Delta}$ from Equation 18, which depends on the estimated demand parameters α and δ. The partial derivatives are potentially jointly determined with the participation decisions. To avoid endogeneity, I use the estimated cross-price derivatives from the year before the policy implementation.

A crucial concern is the number of rivals that should be considered as "close". I propose a method that combines the structural model with market data. The number of close rivals considered by players is the one which minimizes the following criterion function:

$$\underset{k\in\{0,..,N\}}{\arg\min}\, Q = \sum_{N}\sum_{j\in\mathcal{F}_f}\left(\hat{\Pi}_j(k) - \hat{\Pi}_j^*\right)^2 \tag{23}$$

where $\hat{\Pi}_j^*$ is the estimated profit of program j under the observed market conditions, while $\hat{\Pi}_j(k)$ is the estimated profit assuming they track their k close rivals. The rationale is that colleges might not be able to predict the behavior of all other players. When colleges compute profits, I assume they have perfect information about demand parameters (α, δ) and marginal costs c of every program.

The criterion function is the sum of squared deviations for the profits of colleges that offer an Education program. Colleges that don't offer an Education program are not considered, as they don't take any discrete choice. The deviation boils down the model fit of the discrete decisions taken by colleges. The identity of the players, however, is crucial in computing the function, as some colleges are more pivotal than others.

6 Results

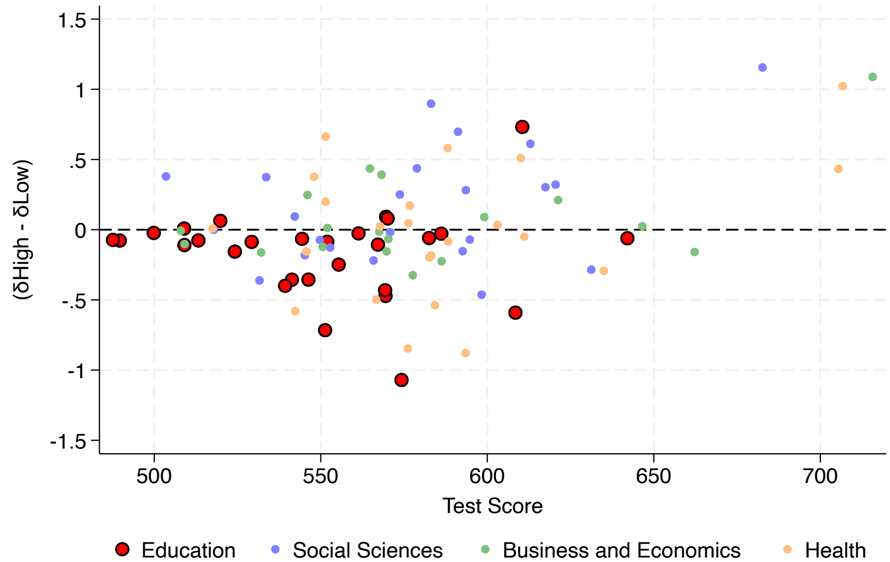
In this section I present the results of the estimation of the model. Section 6.1 discusses the estimated parameters of the demand estimation. Section 6.2 provides evidence of the goodness-of-fit of both the general equilibrium model and the potential outcomes model. Section 6.3 presents the results of the equilibrium selection criterion function.

6.1 Parameter Estimates

Results from the Demand estimation can be found in table D1. Several features can be highlighted. First, the coefficient for the policy is positive and significant, which is expected as it reflects the utility generated by the exogenous variation in the amount of tuition covered by the government. The coefficient is more than three times as high for low income students, implying a higher disutility for prices. Second, students sort into colleges based on their test scores and their socioeconomic status (in the model, reflected by a binary variable for having attended a private high school). Students with higher test scores have higher preference for elite colleges, while students who attended a private high school have a higher preference for a subgroup of private colleges, which are higher quality than the average public college, and also the most expensive ones in the market.

Figure 8 plots the difference in mean utilities for High and Low Income students, for different majors ($\delta_j^{\text{High}} - \delta_j^{\text{Low}}$). While High Income students tend to have a higher preference for most fields, the estimated difference for Education programs tends to be negative, which indicate that Low Income students tend to have a higher preference for Education programs than High Income students. Combined to a higher disutility for prices, this implies that Low Income students are more likely to enroll in Education programs than High Income students, which is consistent with the observed enrollment patterns.

Figure 8: Difference in Mean Utilities for High and Low Income Students



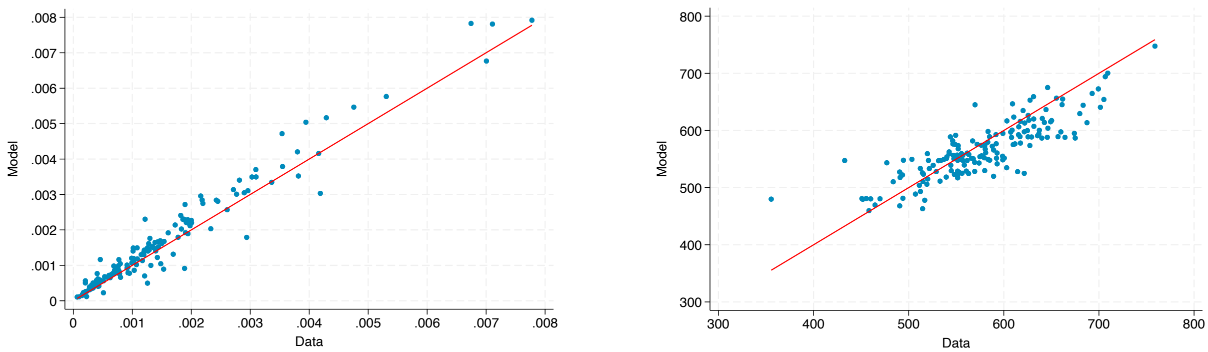
NOTES: This figure plots the difference in (standardized) mean utilities between High and Low Income students. The x-axis corresponds to the program's selectivity (in terms of the average tests scores at the University Entrance Exam), while the y axis corresponds to the difference in mean utilities ($\delta_j^{\text{High}} - \delta_j^{\text{Low}}$). The programs are grouped by their field of study.

6.2 Model Fit

Evidence of the model fit for the demand estimation can be found in Figure 9. It successfully matches programs' market shares, as well as the individual characteristics of students enrolled in each program. Some features limit the goodness-of-fit from the structural model. Students apply to both in and off platform programs, and aftermarket frictions are substantial (Kapor et al., 2024). Also, to ease the computational burden, I collapsed multiple degrees into a unique college-field option.

Figure 9: Model Fit - Demand Estimation

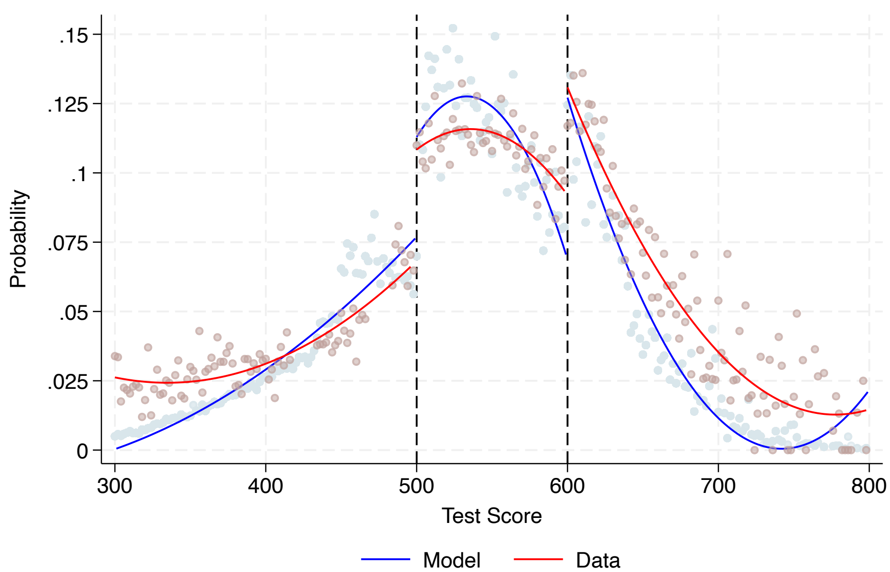
(a) Market Shares **(b)** Test Scores



NOTES: These figures show the results for the model fit of the demand estimation. The x-axis corresponds to observed values, while the y-axis corresponds to predicted values. The dashed line shows the 45 degree line. In each plot, a point corresponds to the average value for a given program.

The model can also successfully replicate the discontinuities generated by the admission and the scholarship rules (the 500 and 600 points thresholds), which can be seen in Figure 10, which plots the enrollment probabilities at Teaching Degrees.

Figure 10: Model Fit - Enrollment at Teaching Degrees

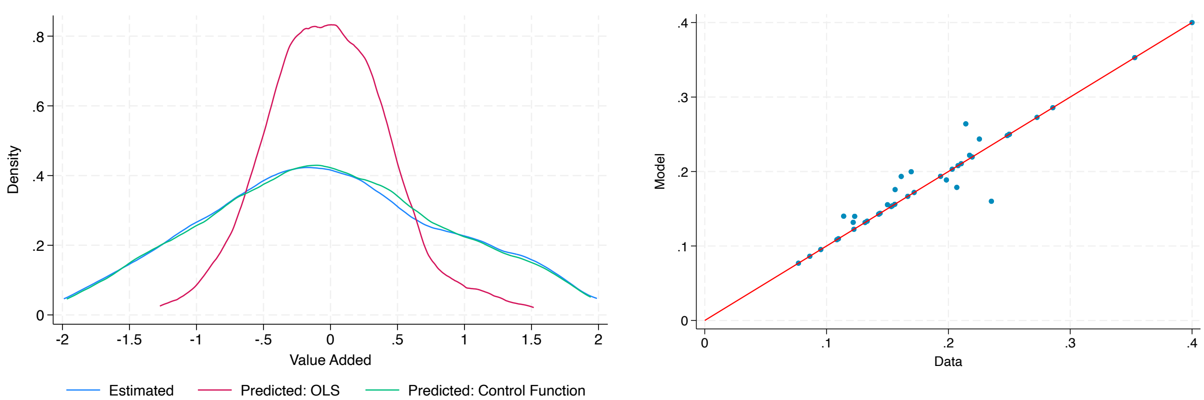


NOTES: This figure shows the enrollment probabilities in Teaching Degrees. The x-axis corresponds to the University Entrance Exam score, while the y-axis corresponds to average probability of enrollment at a Teaching Degree. The dashed lines correspond to the admission rule (500 points) and the scholarship rule (600 points). The red dots plot the mean enrollment for bins of students at every 2 Test Score points, while the blue dots represent the predicted enrollment probabilities from the model for the same groups.

Results of the model fit for the outcome model can be found in Figure 11. Inspection of Figure 11a shows that the OLS model does a poor job in predicting Teacher Value Added. However, the Control Function approach successfully corrects for the selection bias, with the distribution of the predicted values closely matching the distribution of the estimated Teacher Value Added. The correlation between the estimated Value Added and the OLS prediction is 0.37, while the correlation with respect to the Control Function prediction is 0.92. Figure 11b shows that the Control Function approach does a good job in predicting the average turnover of Education programs. At the program level, the correlation between observed turnover and the OLS prediction is 0.74, while the correlation with respect to the Control Function prediction is 0.86.

Figure 11: Model Fit - Outcomes

(a) Teacher Value Added **(b)** Turnover

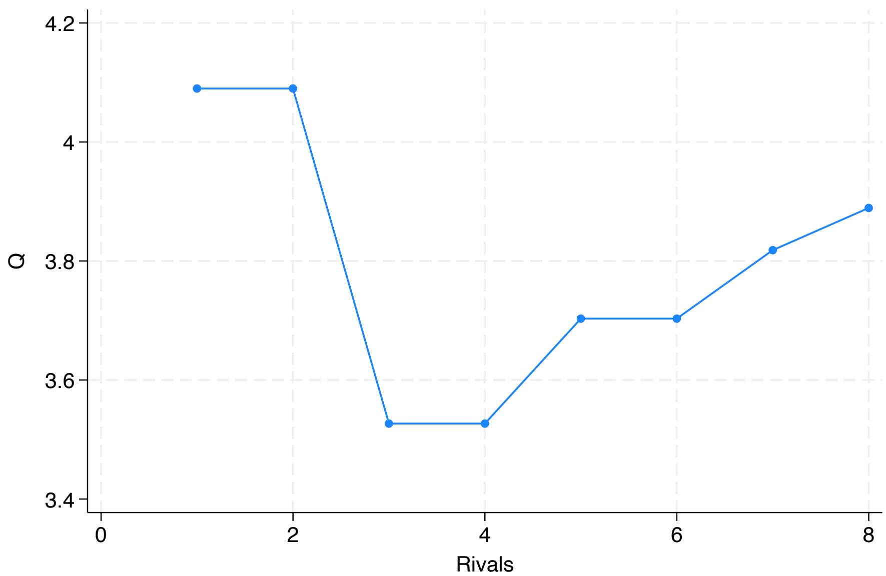


Notes: These figures show the model fit for estimating the Outcome equation following the Control Function approach. Figure 11a shows the distribution for (a) the estimated Teacher Value Added for students who enrolled in an Education program and later worked as teachers, (b) the OLS prediction based on pre-college observable characteristics, and (c) the Control Function prediction based on pre-college observable characteristics. Figure 11b shows the model fit for the Turnover outcome. Each value corresponds to the average value for a given program.

6.3 Equilibrium Selection

Figure 12 shows the results of estimating Equation 23 for different values of k. First, note that the criterion function is U-shaped, and the minimum is reached for $k = 3, 4$ (the same market structure is reached). This indicates that colleges do indeed track the actions of close rivals, but to assume they solve for a Nash Equilibrium would imply forcing them to behave in a more sophisticated way that data shows. This notion, therefore, better captures the heuristic behavior of colleges. In particular, it captures the fact that programs compete in a highly segmented market, and 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. Second, the minimum is reached at a value of k that is small enough to be computationally feasible. I set $k = 4$ for the counterfactual simulations.

Figure 12: Criterion Function



NOTES: These figure shows the results for the Criterion function for selecting the number of optimal close rivals. The x-axis shows the number of close rivals, while the y-axis shows the value of the criterion function. The dashed line shows the value of the criterion function for the observed data.

7 Counterfactuals

In this section, I use the model to study the optimal design of the Teacher Recruitment Policy by simulating alternative policy rules. Section 7.1 show the results of the policy decomposition, where I study the effect of each individual component in isolation. Section 7.2 presents the results of a grid of counterfactual policies, where both components vary. Motivated by the results of Section 3, in Section 7.3 I simulate the counterfactual rules of the previous subsection for the case of a Means-based policy, where the scholarship is only offered to low-income students.

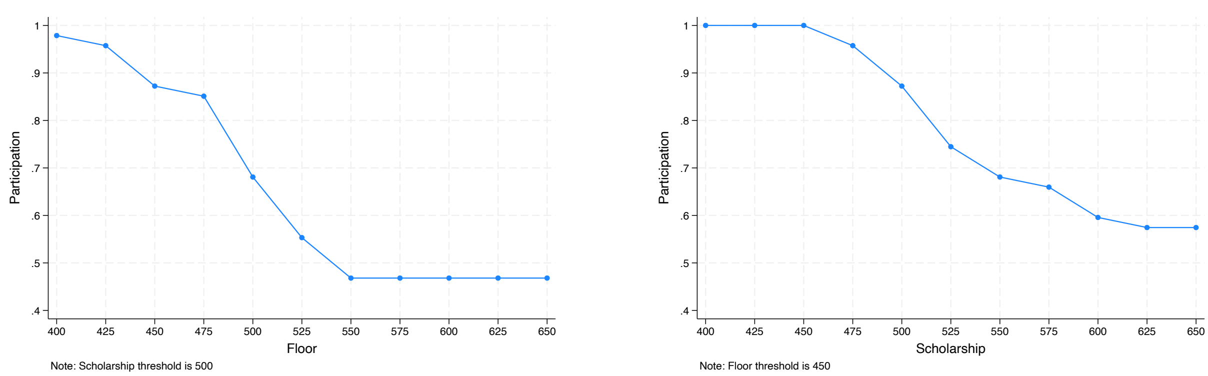
7.1 Decomposing the Policy

To study the effect of each individual component in isolation, first I simulate counterfactual scenarios where I vary one of the components in isolation. Note that, in order to generate variation in participation, both components need to be present: in absence of a floor rule, every program weakly prefers to participate in the policy and, in absence of a scholarship rule, every program weakly prefers to opt out. Therefore, I proceed to fix in each case the rule at 400, which generates sufficient variation in both the colleges and the students' decisions.[33]

Results can be found in Figures 13, 14 and 15. The first one shows the participation decision of all Education programs under counterfactual floor (Figure 13a) and scholarship (Figure 13b) threshold rules. For the floor counterfactuals, participation drops sharply, and no program chooses to freely participate for values above 550, where only public universities participate. As I don't model exit, I assume programs in public colleges will remain even though for implausible high floor values they will lose virtually all enrollment. Therefore, these Figures serve to delimit the region of plausible policy rules. For the scholarship value, however, the effect is more gradual. As the scholarship rule increases, the lowest quality programs are the first to opt out, as they fail to attract enough students to compensate for the ones that they lose due to the floor. For a scholarship rule of 600, still some high quality private universities opt-in, as they have sufficiently high cutoff scores.

Figure 13: Simulated Participation

(a) Alternative Floor Rules **(b)** Alternative Scholarship Rules



NOTES: These figures show the participation decision of Education programs under counterfactual policy rules. Figure 13a shows the effect of varying the floor while keeping the scholarship threshold constant, while Figure 13b shows the effect of varying the scholarship threshold while keeping the floor constant.

Figure 14 shows the effect of the policy on the market shares of Education programs. Figure 14a shows the effect of varying the floor while keeping the scholarship threshold constant, while Figure 14b shows the effect of varying the scholarship threshold while

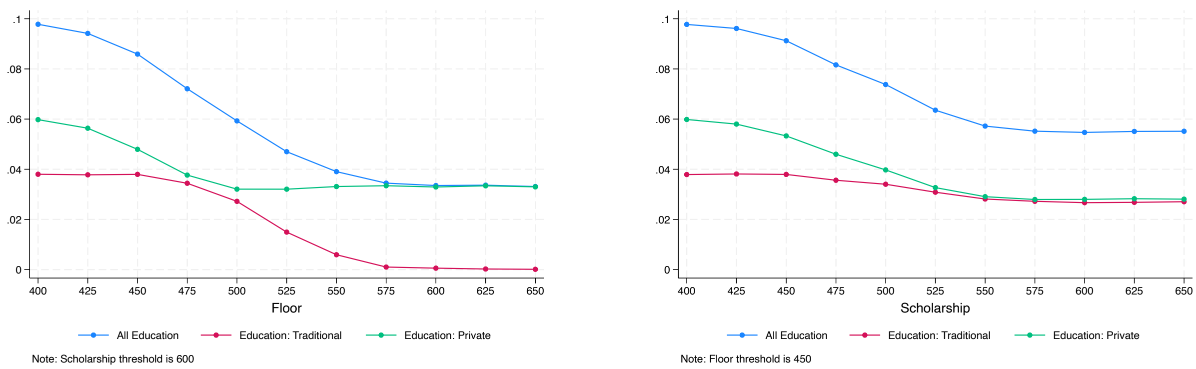
[33] For the floor counterfactuals, the scholarship rule is effectively at the floor.

keeping the floor constant. It can be shown from Figure 14a that the private colleges preserve mostly a constant market share, as they quickly opt out from the policy, and they don't succeed in capturing students from other fields. The traditional colleges remain by design, and therefore lose market share. For a sufficiently high floor, their market share drops virtually to zero, and the market share of all Education programs converges to the one of Private colleges. From Figure 13b 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 14: Simulated Market Shares

(a) Alternative Floor Rules

(b) Alternative Scholarship Rules

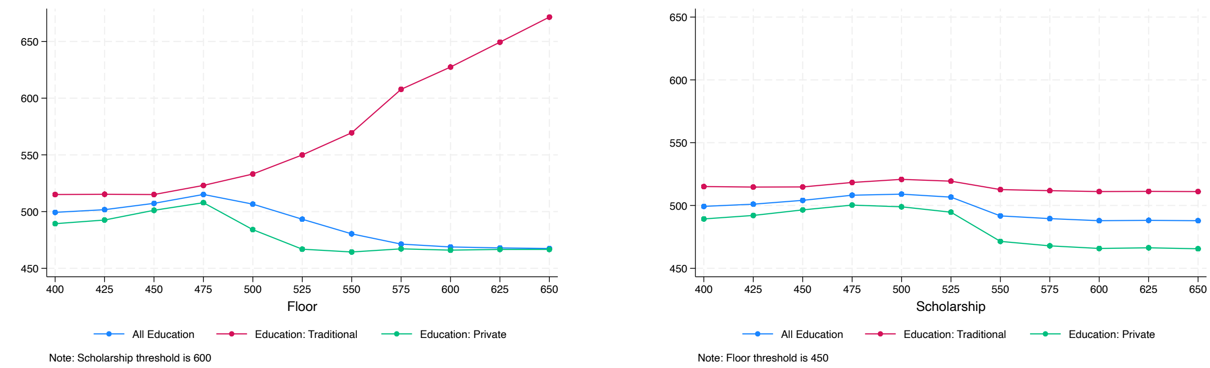


NOTES: These figures show the market shares of different set of programs under counterfactual policy rules. Figure 13a shows the effect of varying the floor while keeping the scholarship threshold constant, while Figure 13b shows the effect of varying the scholarship threshold while keeping the floor constant.

Figure 15 shows the average test scores of Education programs under counterfactual policy rules. Figure 15a shows that average test scores in public universities raises sharply with the floor, as participation in the policy is fixed by design. However, as their market share declines as sharply, overall test scores first increases (due to a positive composition effect) but then decline and converge to the ones of private colleges. For the scholarship counterfactuals (Figure 15b), first there is a slight increase in test scores (for sufficiently low scholarship thresholds, the attracted students are below-average), while the decline coincides with private colleges opting-out, since they fail to attract students with high enough scores. The traditional colleges, however, are able to retain most of their students, and therefore their average test scores remain mostly constant.

Figure 15: Simulated Test Scores

(a) Alternative Floor Rules **(b)** Alternative Scholarship Rules



NOTES: These figures show the average test scores of Education programs under counterfactual policy rules. Figure 13a shows the effect of varying the floor while keeping the scholarship threshold constant, while Figure 13b shows the effect of varying the scholarship threshold while keeping the floor constant.

7.2 Optimal policy

While Figures 13, 14 and 15 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 16. I omit simulations for scholarship parameters below floor parameters, as they generate virtually the same equilibrium as in the case they are equal.

Figure 16a shows that participation varies dramatically over the policy configuration, as almost all Education Programs opt-in for low Floor-Scholarship combinations, while for a considerable region only traditional colleges participate. Other fields react to the demand shock for Education programs by lowering tuition by a magnitud of 0-10%, depending on the rule. Therefore, a model that would omit general equilibrium effects would overstate the true effect of the policy.

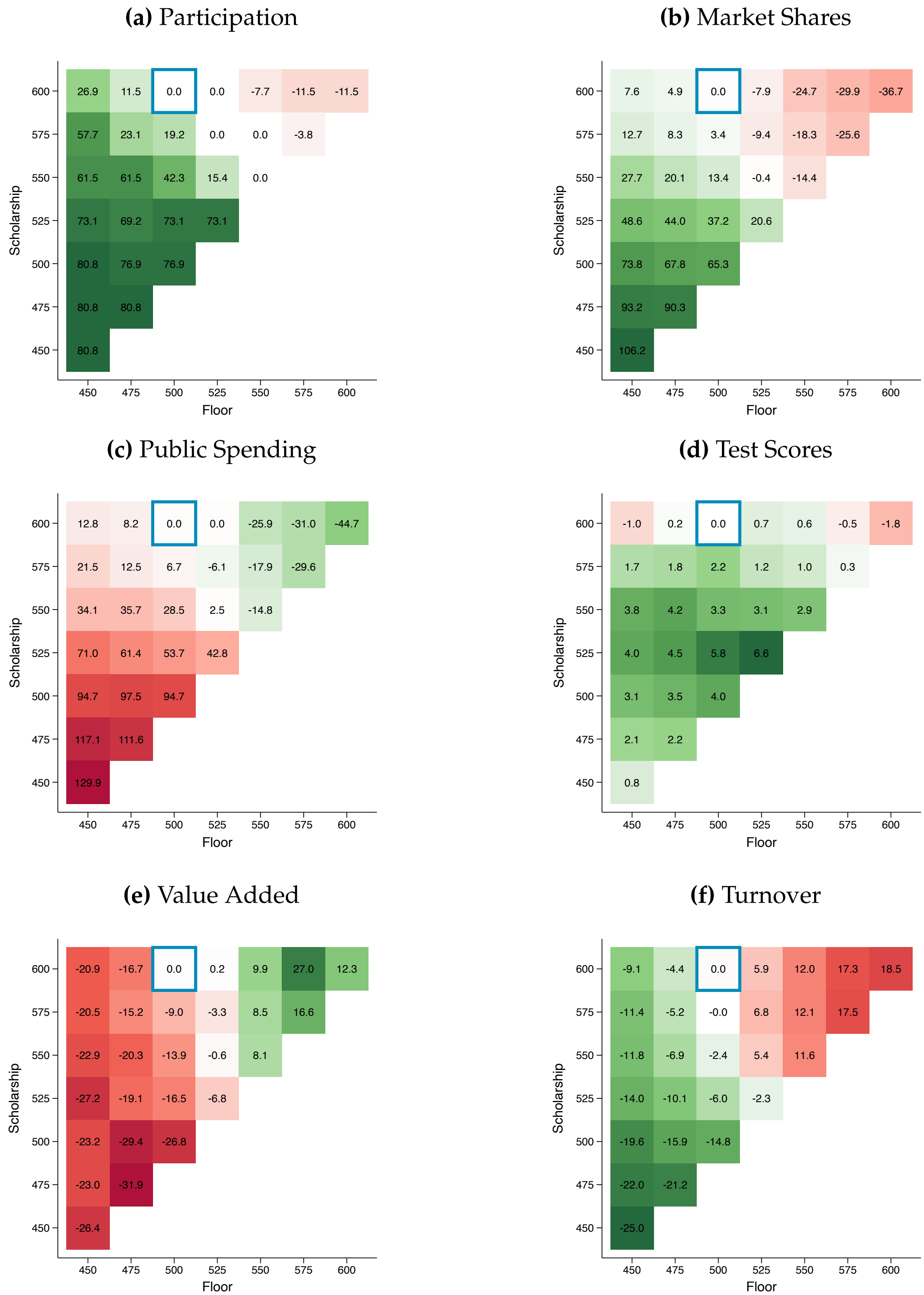
Figure 16b shows that Market Shares find their maximum for the lowest combination of floor and scholarship parameters, while their minimum for the highest floor-scholarship combination. The case of test scores, which can be seen in Figure 16d is non-monotonic. There are potential gains of decreasing the floor and scholarship rules. For example, if lowering the floor to 450, the maximum test score gains will be at a 525 scholarship threshold. 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, and the ones that are attracted don't offset the below-average students drawn by the low floor.

The combination implies an increase both in average test scores and in market shares compared to the observed policy. However, as can be seen in Figure 16c, this configuration will be dramatically costlier, as most of the students pursuing Education programs would have a full scholarship, therefore the policy maker should trade-off quantity, quality and cost in deciding the optimal policy. Meanwhile, maximum gains are found for the {525;525} combination, which implies a 6.6% increase in average test scores. There are combinations that imply a gain in average test scores in a cost-saving way, but the price to pay is lower market shares.

For the predicted outcomes under the model defined by Equation 19, a couple of things are worth noticing. First, as shown in Figure 16e, the pattern for Value Added does not follow the one for Test Scores. An explanation of this feature can be rationalized by Figure D1, which plots the distribution of Program Value Added, which are the fixed effects recovered when estimating Equation 19 with Teacher Value Added as the dependent variable. The increase in market share of Education programs that results of lowering the floor is driven by those programs who have spare capacity in the baseline, which are the lowest quality programs. While most programs don't have a statistically significant impact of teacher effectiveness, there is a subset of programs with a negative estimated fixed effect, and increasing the market share of those programs, even though it increases the average test scores of students enrolled in education programs, it implies a negative composition effect in teacher effectiveness.[34] Increasing the average teacher value added can be achieved only with a strict floor rule. However, Figure 16f reveals that reduced market shares is not the only cost to pay: the estimated turnover for those students enrolled in Education programs will be higher.

[34]This result is consistent with the approach of Neilson et al. (2022), which uses a regression discontinuity design to estimate the value added of teaching programs, compared to the next best alternative. Results also point to a significant share of programs with negative value added.

Figure 16: Simulated Outcomes



NOTES: This figure shows the results of counterfactual simulations under a grid of policy parameters. In all cases, the value is the percentage difference with respect to the observed policy. 16a shows the difference in participation rates, 16b shows the difference in market shares, 16c shows the difference in the total amount of public spending, 16d shows the difference in average test scores, 16e shows the difference in value added and 16f the difference in turnover rates.

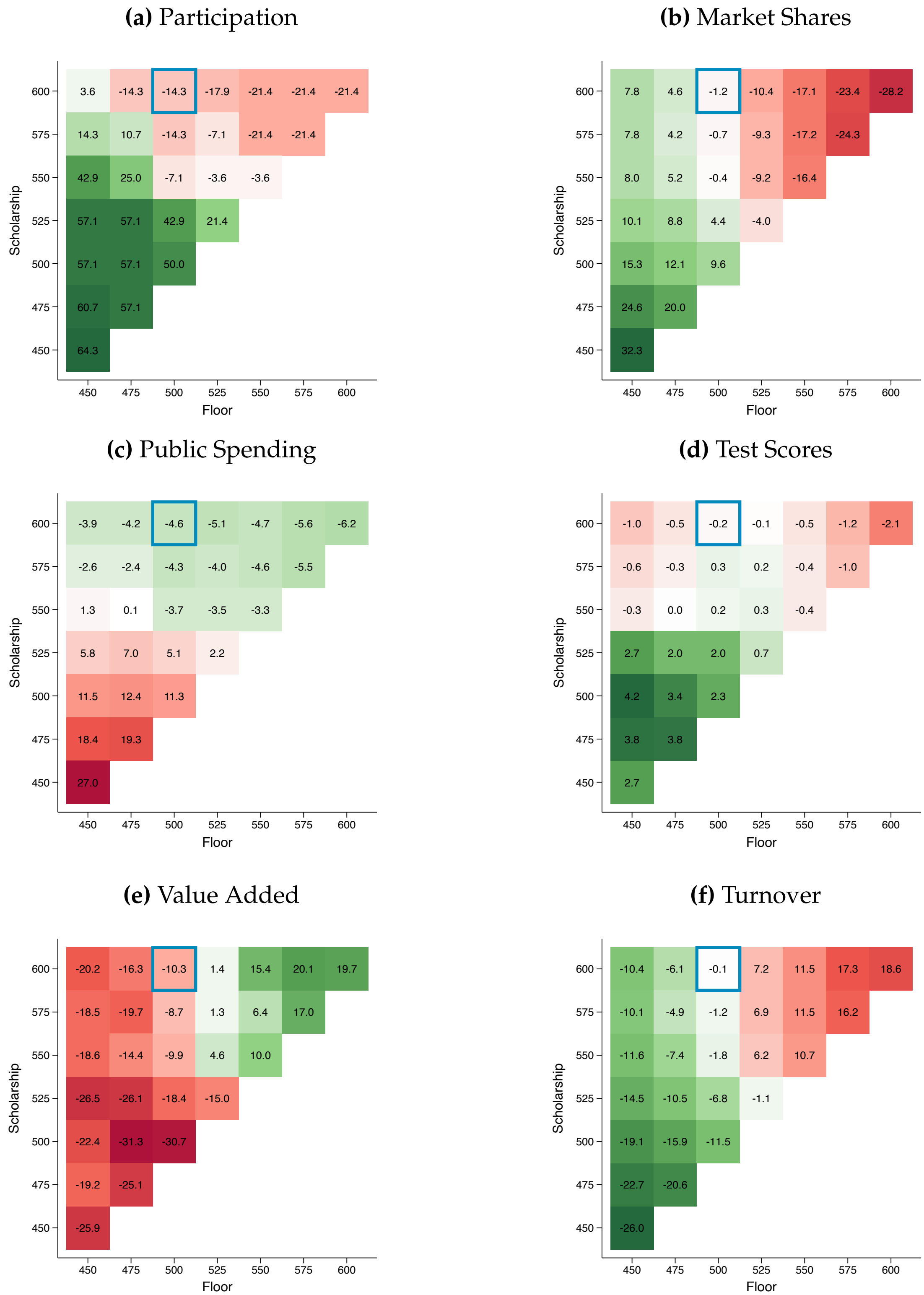
7.3 Means-based policy

There are multiple reasons for why implementing a means-based policy can be desirable not only for equity concerns, but also for efficiency. First, results from Table 2 show that the effect on enrollment for Low income students is double the effect for High income students. Results from the Demand Estimation (found in table D1) show that the Low income students are three times more price sensitive. Therefore, they are more sensible to switch their enrollment decisions because of the policy. Second, as shown in Table 2, Low income students are disproportionately drawn from non-enrollment, while High income students are drawn from other fields. That means that targeting at Low income students would put less competitive pressure on other fields, which has been shown to reduce the overall effect of the policy. Third, from the share of Low income students that substitute from other fields, many already have partial funding, therefore the increase in public spending per scholarship will be less than compared to High income students.

Results are shown in Figure 17, where each cell shows the percentage difference with respect to the observed (not Means-based) policy. First note that a means-based policy under the observed Floor-Scholarship configuration would lower market shares and test scores, at virtually the same cost. However, the setting $\{475; 550\}$ would increase market shares without affecting test scores and at no additional cost, making it a more efficient way of using public funds.

In terms of the Value Added - Turnover trade off, there are efficiency gains of implementing a Means-based policy. For example, instead of implementing a non-means-based policy in the rules $\{575; 575\}$, which imply a reduction of 25.6% in enrollment, a 16.6% increase in Value Added and a 17.5% increase in Turnover, a Means-based policy in the same rule implies a reduction of 24.3% in enrollment, a 17% increase in Value Added and a 16.2% increase in Turnover. Several other combinations can also achieve efficiency gains. However, it's worth noticing that maximum Value Added gains (of 27%) are achieved for a non-means-based policy.

Figure 17: Simulated Outcomes (Means-based Policy)



NOTES: This figure shows the results of counterfactual simulations under a grid of policy parameters, for the case of a Means-based policy. In all cases, the value is the percentage difference with respect to the observed policy. 17a shows the difference in participation rates, 17b shows the difference in market shares, 17c shows the difference in the total amount of public spendig, 17d shows the difference in average test scores, 17e shows the difference in value added and 17f the difference in turnover rates.

8 Conclusion

This paper studies the optimal design higher education policies targeted at strategic programs. 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 a scholarship, and (ii) an admission rule that restricts students from enrolling in certain programs. 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. Moreover, this increase in the composition of students sorting into teaching degrees lead to gains in the labor market, as measure by Teacher Value Added and Teaching Skills.

To better understand the mechanisms that drive the observed equilibrium, and to simulate counterfactual policy rules, I build a supply and demand model of higher education, where the government sets policies over programs, colleges decide on participation and tuition, and students make college-major choices. The model embeds a novel approach to solving discrete-continuous games, in which the bounded rationality of colleges is captured by the fact that they might be able to correctly predict only the actions of their closes rivals, while they might make behavioral mistakes when predicting the actions of the whole industry. Results show that indeed colleges behave in a way that is consistent with bounded rationality, as the model fit decreases when increasing the level of sophistication of colleges.

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 the number of graduates from Education degrees. A subset of teaching programs produce below-average teachers, even when attracting above-average students. The policy-maker also faces a trade-off between Teacher Value Added and Turnover, since higher Value added teachers also are more likely to exit the profession. Exploiting several mechanisms, a Means-based policy could achieve a higher effect on enrollment, while keeping the same fiscal burden. Also, there can be efficiency gains, in terms of additional gains in Value Added and reduced increases in Turnover.

There is scope for future work in many dimensions. With respect to the equilibrium, players could be endogenously more or less sophisticated, depending on the type of policy they are facing. Also, there is space for further refining the policy, going beyond a Means-based scheme.

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A Appendix: Descriptives

Table A1: Participant teacher colleges

	Public		Private		
	BVP	All	BVP	All	%
2010	0	22	0	40	0
2011	22	22	13	43	53.8
2012	22	22	12	42	53.1
2013	22	22	13	40	56.5
2014	23	23	11	36	57.6
2015	22	23	9	31	57.4

NOTES: These table shows participation in the policy for public and private universities, from 2010 (the year before implementation) to 2015.

Table A2: Descriptive statistics, degrees

	2009	2010	2011	2012	2013	2014	2015
All							
Colleges	65	63	63	65	62	63	63
Degrees	2762	2855	3004	3023	2903	3029	3013
Santiago	.314	.323	.326	.330	.369	.356	.349
Tuition	4235	4206	4216	4326	4450	4407	4416
Full Capacity	.455	.399	.359	.326	.332	.340	.415
Has Cutoff	.715	.711	.621	.727	.732	.654	.708
Cutoff Score	485	493	502	491	494	500	488
Inside Platform							
Colleges	25	25	25	33	33	33	33
Degrees	1009	1014	1020	1407	1477	1501	1514
Santiago	.227	.236	.231	.322	.327	.328	.323
Tuition	4171	4178	4255	4736	4815	4794	4850
Full Capacity	.598	.585	.527	.464	.495	.525	.601
Has Cutoff	1	1	1	1	1	1	1
Cutoff Score	527	527	526	516	514	509	509
Outside Platform							
Colleges	40	38	38	32	29	30	30
Degrees	1753	1841	1984	1616	1426	1528	1499
Santiago	.364	.372	.375	.337	.413	.383	.374
Tuition	4275	4222	4196	3936	4032	3955	3889
Full Capacity	.373	.296	.273	.205	.162	.159	.227
Has Cutoff	.552	.552	.427	.489	.455	.314	.413
Cutoff Score	449	465	479	453	458	476	444

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 A3: Descriptive statistics, students

	2009	2010	2011	2012	2013	2014	2015
Enrollment							
N Students	237774	246007	245278	234033	239125	238098	252275
Enrolled in platform	.206	.205	.203	.300	.311	.318	.309
Enrolled out of platform	.389	.404	.424	.344	.350	.344	.341
Not enrolled	.403	.389	.371	.354	.337	.337	.349
Demograhics							
Family Income	3.1	3.2	3.3	3.5	3.6	3.9	4
Private School	.105	.100	.101	.112	.111	.113	.111
Private Health	.283	.268	.265	.275	.273	.274	.270
Father With College	.169	.161	.163	.175	.175	.177	.177
Mother Employed	.390	.388	.404	.417	.437	.461	.465
Field							
Business	.127	.126	.127	.126	.129	.134	.140
Farming	.028	.025	.024	.023	.023	.021	.024
Art and Architecture	.060	.056	.052	.050	.050	.051	.052
Basic Sciences	.033	.031	.030	.032	.034	.036	.035
Social Sciences	.090	.089	.087	.088	.084	.086	.088
Law	.045	.040	.038	.037	.035	.036	.037
Education	.143	.145	.140	.132	.112	.106	.108
Humanities	.012	.011	.011	.011	.012	.011	.011
Health	.195	.209	.218	.228	.216	.213	.211
Technology	.256	.257	.261	.261	.292	.292	.282

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.

B Appendix: RD

Table B1: RD estimates of teacher enrollment, epanechnikov kernel

	Participant		Non-Participant	
	(1)	(2)	(3)	(4)
Enrollment	0.052***	0.038***	-0.019***	-0.003
	(0.003)	(0.006)	(0.003)	(0.002)
Cutoff	500	600	500	600
Observations	71160	42674	92630	40859
Bandwidth	40.1	36	52.9	35
Baseline	.004	.086	.067	.014

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

Table B2: RD estimates of teacher enrollment, uniform kernel

	Participant		Non-Participant	
	(1)	(2)	(3)	(4)
Enrollment	0.051***	0.040***	-0.018***	-0.002
	(0.003)	(0.006)	(0.004)	(0.002)
Cutoff	500	600	500	600
Observations	61180	37076	67172	50776
Bandwidth	34.1	32	37.8	43.4
Baseline	.004	.086	.067	.014

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

Table B3: RD estimates of teacher enrollment, with controls

	Participant		Non-Participant	
	(1)	(2)	(3)	(4)
Enrollment	0.052***	0.034***	-0.018***	-0.003
	(0.003)	(0.007)	(0.003)	(0.002)
Cutoff	500	600	500	600
Observations	71305	37155	99297	40425
Bandwidth	42	34	60.8	36.7
Baseline	.004	.086	.067	.014

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)
Enrollment	0.052***	0.036***	-0.018***	-0.003
	(0.003)	(0.006)	(0.003)	(0.002)
Cutoff	500	600	500	600
Observations	78258	43528	104921	41872
Bandwidth	44.2	37.1	60.8	35.7
Baseline	.004	.086	.067	.014

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)
Enrollment	0.053***	0.040***	-0.018***	-0.002
	(0.003)	(0.005)	(0.003)	(0.002)
Cutoff	500	600	500	600
Observations	87686	58173	87686	58173
Bandwidth	50	50	50	50
Baseline	.004	.086	.067	.014

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

Table B6: RD estimates of teacher enrollment, Bandwith 25

	Participant		Non-Participant	
	(1)	(2)	(3)	(4)
Enrollment	0.053***	0.031***	-0.008*	-0.004
	(0.004)	(0.008)	(0.005)	(0.003)
Cutoff	500	600	500	600
Observations	44732	28894	44732	28894
Bandwidth	25	25	25	25
Baseline	.004	.086	.067	.014

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

Table B7: RD estimates on observable characteristics

	All		Enrolled		Teaching students	
	(1)	(2)	(3)	(4)	(5)	(6)
	Estimate	SE	Estimate	SE	Estimate	SE
Female	0.00438	(0.00987)	0.00848	(0.0108)	–0.0604**	(0.0279)
High School GPA	–0.514	(1.55)	–0.474	(1.65)	–7.49	(4.76)
Public HS	0.00203	(0.00692)	–0.000500	(0.00744)	–0.00391	(0.0280)
Voucher HS	0.00624	(0.00862)	0.00580	(0.00918)	0.00768	(0.0254)
Private HS	–0.00948	(0.00726)	–0.00952	(0.00791)	–0.00772	(0.0178)
Santiago	0.00958	(0.00901)	0.0210**	(0.0106)	0.0429	(0.0273)
Family Income	–0.0364	(0.0506)	–0.105*	(0.0588)	–0.158	(0.137)
Private Health	–0.0159*	(0.00873)	–0.0148	(0.00977)	–0.0420	(0.0281)
Father With College	–0.0238***	(0.00845)	–0.0188**	(0.00913)	–0.0396*	(0.0227)
Mother With College	–0.0220***	(0.00745)	–0.0285***	(0.00852)	–0.0322	(0.0225)
Father Employed	–0.00642	(0.00717)	–0.00482	(0.00740)	0.00822	(0.0283)
Mother Employed	–0.0158*	(0.00921)	–0.0158	(0.0103)	–0.0363	(0.0318)
N	245,278		154,113		17,030	

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 programs. 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. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B8: Placebo tests

	2011		2010	
	(1)	(2)	(3)	(4)
Enrollment	-0.003	0.000	-0.000	-0.005
	(0.005)	(0.008)	(0.004)	(0.005)
Cutoff	550	650	500	600
Observations	52540	20802	67191	50623
Bandwidth	67.8	29.2	37.7	43
Baseline	.079	.080	.049	.087

NOTES: This table shows the estimates from four placebo tests. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B9: RD estimates of retaking University Entrance Exam

	(1)	(2)
Retake	-0.006	-0.007
	(0.006)	(0.008)
Cutoff	500	600
Observations	88599	58627
Bandwidth	50.4	50.4
Baseline	.166	.228

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. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B10: RD estimates of application at teacher colleges

	Any choice		First choice	
	(1)	(2)	(3)	(4)
Applied	0.083***	0.013	0.040***	0.032***
	(0.005)	(0.010)	(0.004)	(0.006)
Cutoff	500	600	500	600
Observations	81960	33800	78258	48264
Bandwidth	46.1	28.9	44.4	41.2
Baseline	.081	.220	.049	.106

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. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

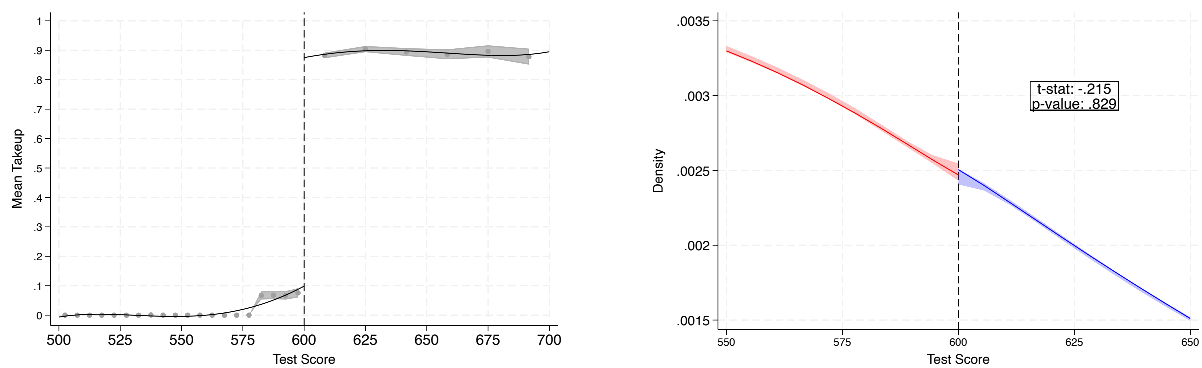
Table B11: RD estimates by income, 500 points cutoff

Dep. Var: *Enrollment*	(1) Estimate	(2) SE	(3) Observations	(4) Bandwidth	(5) Baseline
Panel A: Low Income					
Education (Participant)	0.057***	(0.003)	58186	42.3	.004
Education (Non-Participant)	–0.018***	(0.004)	72632	54.4	.070
Other Bachelor	0.001	(0.009)	43874	31.7	.248
Short Cycle Program	–0.017**	(0.008)	52814	38.3	.281
Not Enrolled	–0.020**	(0.009)	51931	37.7	.387
Panel B: High Income					
Education (Participant)	0.039***	(0.004)	21366	53.3	.003
Education (Non-Participant)	–0.015***	(0.006)	25589	64.2	.055
Other Bachelor	0.017	(0.015)	20318	50.8	.316
Short Cycle Program	0.001	(0.013)	19066	47.1	.248
Not Enrolled	–0.032***	(0.012)	29725	74.7	.352

NOTES: This table shows the estimates from the RD design. Estimation is based on the full sample of test takers, while the effective number of observations used in each regression comes from optimal bandwidth selection resulting from minimizing the mean-squared error (Calonico et al., 2015).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure B1: Robustness checks

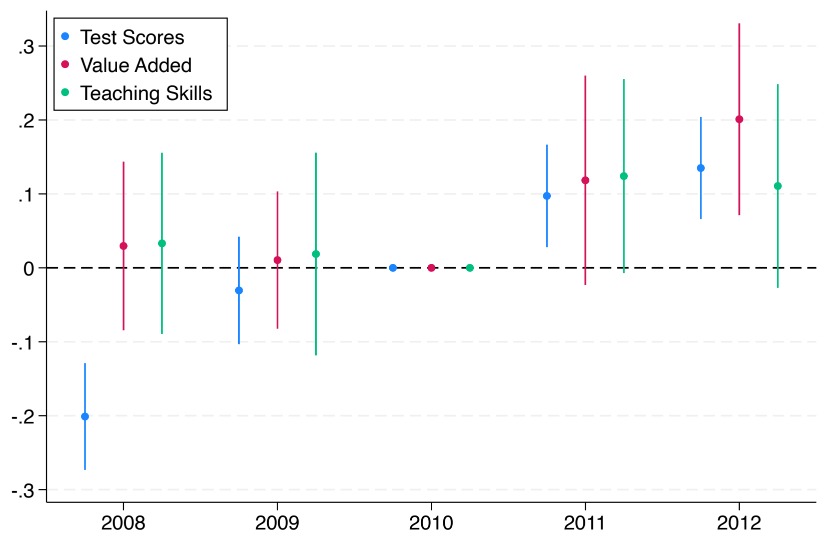
(a) Scholarship Takeup　　　　**(b)** Test Score density



NOTES: Figure B1a plots mean scholarship takeup among all test takers within bins of test scores, with a quadratic fit on each side of the 600 points threshold. Figure B1b shows the kernel density estimation of test scores, and the results from the manipulation test of Cattaneo et al. (2020). Both figures are obtained using the 2011 data.

C Appendix: DID

Figure C1: Dynamic DID estimates of performance



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. The sample is composed of primary school teachers from the 2008-2012 cohorts. For Test Scores, it includes teachers from every grade, for Value Added, it includes 6th and 8th grade teachers. For Teaching Skills, it includes teachers from every grade in public schools. In all cases, robust standard errors are computed. Point estimates as well as 95% confidence intervals are shown.

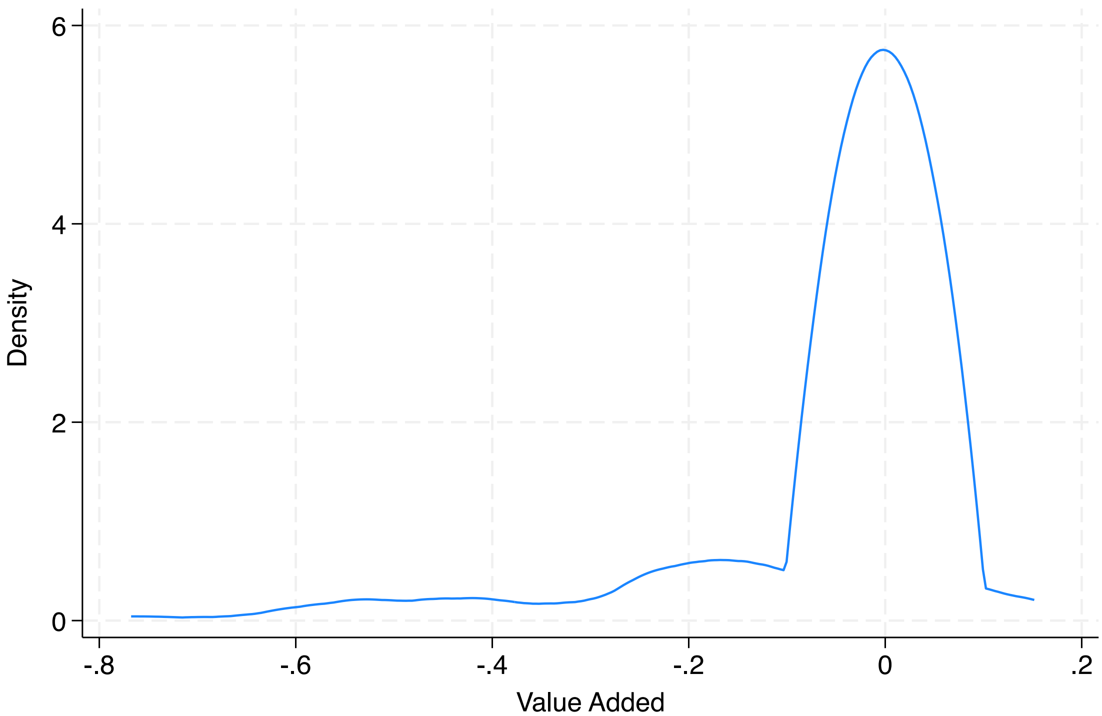
D Appendix: Structural Estimation

Table D1: Demand Estimation

	Low Income		High Income	
	(1)	(2)	(3)	(4)
	Coefficient	SD	Coefficient	SD
BVP	.5706695	.1288029	.1723161	.0737211
Scholarship	-.1763007	.0578329	.0082801	.0171851
Region	1.615252	.5165182	1.233946	.3388725
Score × Elite	1.785911	.1741288	1.812159	.1046096
Score × Other	.5740744	.1348552	-.0295194	.0744166
Score × G8	1.188781	.197918	.7341746	.0713784
Score × OOP	.150568	.0553	-.3896617	.0386926
Private × Elite	-.2269518	.4249192	.1187289	.1623122
Private × Other	-.5584155	1.062287	-.6914142	.1742171
Private × G8	1.17424	.6324036	1.048946	.1419506
Private × OOP	.1778781	.1869372	-.1476643	.1029858
Region × Score	-.6767057	.0924391	-.5422618	.0574346
Region × Private	.6141254	.945844	.8101693	.0931245
Score × Business	.9770469	.190265	.8114344	.0844157
Score × Health	1.374072	.1706636	1.222963	.0575017
Score × STEM	1.342059	.2123928	.9809303	.0698641
Score × Social	.9428878	.1812397	.6898212	.0589597
Private × Business	.8116881	1.186842	.0306753	.1589345
Private × Health	-.2647985	.4104184	-.4646438	.1343444
Private × STEM	-.3733478	.3954002	-.488538	.1479976
Private × Social	-.0583049	1.792955	.2833681	.1331591
Private × Education	-1.49117	.4913717	-.5991732	.177855
Education × Score	5.083022	1.597586	5.659968	.7480942
Education × Score2	-.2140012	.9163349	-.2555143	.7097575
Education × Score3	-.2126582	.8310266	-.2553726	.7064224
Intercept	.1988708	20.47159	.2270486	2.617208
Intercept: Mother	.1720422	.1193381	.0583678	.0564242

NOTES: This table shows selected estimates of the Demand Estimation.

Figure D1: Program Value Added



NOTES: These figure plots the distribution of Value Added of Education programs, as estimated by the Control Function approach.

E Appendix: RD as Instrument for Prices

Define the utility of enrolling in program j as:

$$U_{ij} = \alpha_j + \beta(1 - \lambda_i)p_j + \epsilon_{ij}$$

where λ_i is the percentage of the tuition covered by the scholarship, which depends on test scores r_i. In the particular case of *Beca Vocación de Profesor*, we have:

$$\lambda_i = \begin{cases} 0 & \text{if } r_i < \bar{r} \\ 1 & \text{if } r_i \geq \bar{r} \end{cases} \tag{24}$$

with $\bar{r}$ as the cutoff for the scholarship. The utility of not enrolling is normalized to zero, $U_{i0} = 0$. Assume that ϵ_{ij} is distributed i.i.d. extreme value. Then, the probability of student i with test score r of enrolling in program j is given by:

$$P_{irj} = \frac{e^{U_{irj}}}{\sum_k e^{U_{irk}}} \tag{25}$$

and the market share for program j of students with score r as

$$\begin{aligned} s_{rj} &= \int_{r_i = r} P_{irj}\,\mathrm{d}i \\ &= \int_{r_i = r} \frac{e^{\alpha_j + \beta(1-\lambda)p_j}}{\sum_k e^{\alpha_k + \beta(1-\lambda)p_j}}\,\mathrm{d}i \\ &= e^{\alpha_j + \beta(1-\lambda)p_j} \int_{r_i = r} \frac{1}{\sum_k e^{\alpha_k + \beta(1-\lambda)p_j}}\,\mathrm{d}i \end{aligned} \tag{26}$$

and therefore:

$$\log s_{rj} = \alpha_j + \beta(1 - \lambda)p_j + \log \int_{r_i = r} \frac{1}{\sum_k e^{\alpha_k + \beta(1-\lambda)p_j}}\,\mathrm{d}i \tag{27}$$

For the outside option, we have

$$\log s_{r0} = \log \int_{r_i = r} \frac{1}{\sum_k e^{\alpha_k + \beta(1-\lambda)p_j}}\,\mathrm{d}i \tag{28}$$

Therefore:

$$\log \frac{s_{rj}}{s_{r0}} = \alpha_j + \beta(1-\lambda)p_j \tag{29}$$

At each side of the threshold, we have

$$\begin{aligned} \lim_{r\to\bar{r}^-} \log \frac{s_{rj}}{s_{r0}} &= \alpha_j + \beta p_j \\ \lim_{r\to\bar{r}^+} \log \frac{s_{rj}}{s_{r0}} &= \alpha_j \end{aligned} \tag{30}$$

which implies

$$\lim_{r\to\bar{r}^+} \log \frac{s_{rj}}{s_{r0}} - \lim_{r\to\bar{r}^-} \log \frac{s_{rj}}{s_{r0}} = -\beta p_j \tag{31}$$

averaging over all degrees, we get

$$\beta = \frac{1}{J} \sum_{j\in\mathbb{J}} \frac{\lim_{r\to\bar{r}^+} \log \frac{s_{rj}}{s_{r0}} - \lim_{r\to\bar{r}^-} \log \frac{s_{rj}}{s_{r0}}}{p_j} \tag{32}$$

If we classify the students in types $l \in (1, ..., L)$ based on observable characteristics, the estimated parameter takes the form:

$$\beta = \frac{1}{L} \sum_{l=1}^{L} \left(\pi_l \frac{1}{J} \sum_{j\in\mathbb{J}} \frac{\lim_{r\to\bar{r}^+} \log \frac{s_{rlj}}{s_{rl0}} - \lim_{r\to\bar{r}^-} \log \frac{s_{rlj}}{s_{rl0}}}{p_j} \right) \tag{33}$$

with π_l as the share of students in type l and s_{rlj} as the market share for program j among students of type l with test score r.

In practice, estimation is done with all students, and a polynomial of the running variable at each side of the threshold is used to isolate the local effect at the discontinuity. In a simplified model with only program fixed effects, the regression takes the form

$$\begin{aligned} D_i = {} & \alpha_j + \beta^- \cdot \mathbf{1}\{r_i < \bar{r}\} \; + \; \beta^+ \cdot \mathbf{1}\{r_i \geq \bar{r}\} \\ & + \sum_{k=1}^{K} \gamma_k^- (r_i - \bar{r})^k \, \mathbf{1}\{r_i < \bar{r}\} \; + \; \sum_{k=1}^{K} \gamma_k^+ (r_i - \bar{r})^k \, \mathbf{1}\{r_i \geq \bar{r}\} \; + \; \varepsilon_i. \end{aligned} \tag{34}$$

where D_i takes value 1 for the chosen program, β^- and β^+ are the intercepts on the left and right of the cutoff, and the polynomial terms $\gamma_k^\pm$ flexibly approximate the smooth conditional mean of D_i on each side. The conditional expectation implied by at $r = \hat{r}$ is

$$\lim_{r \to \bar{r}^-} \mathbb{E}[D_i \mid r] = \beta^- + \sum_{k=1}^{K} \gamma_k^- \cdot 0 = \beta^-,$$

$$\lim_{r \to \bar{r}^+} \mathbb{E}[D_i \mid r] = \beta^+ + \sum_{k=1}^{K} \gamma_k^+ \cdot 0 = \beta^+.$$

Therefore, the RD discontinuity is simply

$$\Delta \;=\; \lim_{r \downarrow \bar{r}} \mathbb{E}[D_i \mid r] \;-\; \lim_{r \uparrow \bar{r}} \mathbb{E}[D_i \mid r] \;=\; \beta^+ - \beta^-. \tag{35}$$

All polynomial terms vanish at $r = \bar{r}$, so the estimated intercept difference $\widehat{\beta}^+ - \widehat{\beta}^-$ is exactly the RD jump $\widehat{\Delta}$. A normalization of $\hat{\beta}^- = 0$ yields $\hat{\beta}^+ = \hat{\beta} = \widehat{\Delta}$.