Education Policy and the Quality of Public Servants[*]

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Abstract

This paper studies the design of higher education policies targeted at improving the recruitment of public servants. I leverage the introduction of a policy in Chile that aimed to increase teacher quality by combining financial incentives and admission standards. Exploiting a sharp assignment rule for financial incentives eligibility, I estimate that, at the threshold, enrollment of high performing students at teacher colleges increased by 42%. For low-income students, two thirds of the increase is due to switching away from non-enrollment. The policy led to a 0.25SD increase in the scores at the college entrance exam, which translated into a 0.11SD increase in Teacher Value Added (TVA). I embed the reduced-form results into a demand and supply model of higher education that incorporates a novel method for solving discrete-continuous games in large markets. Alternative combinations of incentives and admission standards lead to increases of up to 6.6% in the test scores of students enrolled at teacher colleges, and up to 20% in TVA. Targeting the policy to low-income students yields further gains in TVA at no additional cost. To achieve similar gains, the expected wages of graduates from teacher colleges would need to increase by approximately 35%, highlighting the cost-effectiveness of the policy.

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1 Introduction

Increasing the quality of public servants is central to strengthening state capacity and effective public service delivery. This is because government performance depends not only on rules and structures, but also 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, limited use of performance-based incentives, weak accountability and scarce prospects for career development (Besley et al., 2022). While low-skilled workers generally enjoy a public sector wage premium, positions for high-skilled individuals tend to offer below-market wages (Gindling et al., 2020), deterring talented candidates.

Wage-related policies (Behrman et al., 2016, Biasi, 2021, Tincani, 2021, Bobba et al., 2024) and incentive-based reforms (Leaver et al., 2021, Muñoz and Prem, 2024, Muñoz and Otero, 2025) can improve recruitment, but implementation at scale has proven difficult, either because of fiscal constraints or the rigid institutional features of the public sector. This paper highlights an unexplored margin for influencing the quality of the public workforce: the upstream role of higher education in shaping the pool of candidates. While existing research on higher education finance has demonstrated the effectiveness of policies that expand access or completion (Angrist et al., 2014, Cohodes and Goodman, 2014, Solis, 2017, Londoño-Vélez et al., 2020), it has provided little guidance on how policy can be designed to attract talent into strategic fields. I fill this gap in the literature by studying the design of an education policy for recruiting elementary school teachers, one of the largest groups of public servants. I develop an empirical framework that shows how the combination of financial incentives and selectivity measures can improve the pool of students who enroll at teacher colleges, how this translates into better teachers, and how education policy outperforms wage hikes as a recruiting tool.

To establish these results, 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 college entrance exam score and subsequent measures of teacher effectiveness. Second, I provide causal evidence that a policy intervention successfully attracted high-performing students into teaching degrees 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 simulate alternative combinations of financial incentives and admission standards, identifying the configurations that most effectively improve teacher recruitment,

and compare it to counterfactual simulations of wage increases.

The Chilean context offers a unique setting in which to study 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, I exploit the introduction of *Beca Vocación de Profesor*, a policy that combines both financial incentives and selectivity measures to improve the pool of entrants into teaching degrees.

With respect to financial incentives, students who scored above the 80th percentile on the national college entrance exam were eligible for a scholarship that fully covered tuition and fees at eligible teacher colleges. As a selectivity measure, 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 all public universities, while private colleges were given the option to participate. Financial incentives affected choices on both sides of the market: on the demand side, the scholarship aimed to lower financial barriers and attract high-performing candidates into teaching degrees; on the supply side, private universities had to decide on take-up by trading off the potential loss of enrollment from stricter admission standards against the increased demand generated by the scholarship.

In practice, take-up of the policy was low, as only a third of private colleges decided to opt in. 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 scholarship threshold attracts few marginal students and makes the scheme unattractive for private colleges, while a low scholarship threshold would make the program costlier and generate a negative composition effect. Pricing decisions are also crucial: as colleges are multi-product firms, the increased demand for education degrees may prompt universities to adjust tuition not only for their teaching program but also for other degrees.

I begin the empirical analysis by establishing the correlation between pre-college achievement and teacher effectiveness. I estimate Teacher Value Added (TVA) following standard practices in the education literature (Chetty et al., 2014a, Bacher-Hicks and Koedel, 2023), and link teachers with their scores at the National Teacher Evaluation Program, which was specifically designed to measure teaching skills and classroom practices. A simple

regression reveals that a 1 standard deviation (SD) increase in the average between the language and mathematics components of the university entrance exam is associated with a 0.21SD increase in TVA and 0.18SD increase in teaching skills. These results are consistent with the literature, which finds a moderate link between academic achievement and classroom effectiveness (Jackson et al., 2014), and makes a policy based on pre-college achievement ex-ante appealing.

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 two-thirds of the increase is explained by a decrease in non-enrollment. For high-income students, the increase is driven entirely by substitution from other fields.

To assess the effect of the policy on teacher quality, I leverage comprehensive administrative data that track individuals from college through teaching. Using a Difference-in-Differences (DID) approach, I exploit the variation from participating and non-participating colleges, before and after policy implementation. I find that the policy led to an increase of 0.25 SD in the entrance exam scores, which translated into a 0.11 SD increase in TVA and a 0.12 SD improvement in teaching skills.

While the results show that the observed policy was successful in improving teacher recruitment, there are three reasons that motivate a structural approach. First, the reduced-form analysis cannot decompose the relative influence of financial incentives and selectivity in the observed equilibrium. Second, the low participation rate among private colleges highlight the need to account for supply-side responses in policy design, and indicates that there might be margin for improvement when financial incentives and selectivity are combined in an alternative way. Third, a model allows to compare the cost-effectiveness of an education policy with respect to wage increases, one of the most common policies used to improve selection into the public sector.

For these reasons, I develop a static demand and supply model of higher education, in which the government sets financial incentives and admission rules. Private colleges maximize profits and solve a discrete-continuous problem: they set tuition for every offered degree while simultaneously deciding on policy participation. Students maximize utility by choosing among college-degree pairs, trading off attributes such as quality, distance and out-of-pocket fees. Solving for equilibrium in discrete-continuous games

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presents computational challenges in large markets, given the size of the strategy space. I make a methodological contribution by modeling colleges as boundedly rational agents (Simon, 1955) who correctly anticipate the actions of their closest rivals but allow for potential prediction errors regarding distant competitors. I provide a data-driven rule to determine both the identity and number of close rivals each college accounts for, allowing these to vary flexibly across markets of different sizes and varying degrees of concentration. This approach not only reduces computational costs but also better fits the data: a model selection criterion indicates that colleges consider their four nearest competitors when making strategic decisions.

The model allows me to estimate the enrollment distribution under counterfactual policy rules, and to measure the gains in recruitment in terms of pre-college achievement. To translate those gains into teacher quality, I estimate Degree Value Added (DVA), that is, the contribution of each degree to teacher effectiveness. Estimating treatment effects in educational contexts is challenging because of selection bias: students tend to self-select into degrees on the basis of 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 are absent in the case of higher education. I address this issue by using a two-step control function approach (following Heckman, 1979) that allows me to control for unobserved preference parameters that govern selection. Specifically, I use the multinomial logit selection model of Dubin and McFadden (1984) which allows to control for selection on both absolute advantages (high-ability students sort into high-ability degrees) and comparative advantages (a specific student-degree match effect).

Simulation of alternative funding and admission rules reveal that participation decisions are highly sensitive to the policy configuration: while a low scholarship threshold can induce participation of private colleges, a sufficiently strict admission rule will cause most colleges to opt-out. Moreover, universities react to the increase in demand for teaching degrees by lowering tuition of other fields by up to 6%. Estimation without considering supply-side responses will therefore yield biased estimates of the policy impact.

Alternative policy combinations outperform the observed policy in improving the quality of college students that pursue education studies. Maximum gains are reached with a policy that, compared to the benchmark, raises admission standards while lowers the scholarship threshold, leading to an increase of 6.6% in the entrance exam scores of students at teacher colleges. Such a policy, which is targeted at maximizing pre-college achievement, does not maximize teacher quality. That is because most spare capacity comes from low quality teacher colleges, which produce below-average teachers even if enrolling above-

average students. A policy that maximizes TVA must be highly selective: while take-up is reduced for private colleges, the compositional changes in public universities generate an overall positive effect, leading to an increase in 20% in TVA, compared with the baseline. However, the model predicts that high quality teachers are also more likely to leave the profession; thus, maximizing TVA in the short-run might not do so in the medium run. A means-based policy yields additional gains without increasing the overall cost, exploiting the fact that colleges have limited capacity, and low-income students have a higher price sensitivity, a higher preference for Education degrees, and are drawn disproportionately out of non-enrollment, attenuating price responses in non-education degrees.

Finally, I investigate the cost-effectiveness of an education policy comparing it to increasing the expected wages of graduates from teaching degrees, one of the most common policies to improve selection into public service. I find that, to achieve similar gains in recruitment, the expected wages would need to increase by approximately 35%. This is because the market shares of teaching degrees strongly react to wage variations. As colleges face no trade-offs, they have no incentives to increase admission standards, leading to a weak compositional improvement in the wage profile. In addition to the increase in wages, the government would spend a similar amount in subsidizing tuition, as students qualify for other existing means- and merit-based scholarships. Given that wage variations do not impact the productivity of incumbent teachers (de Ree et al., 2018, Bau and Das, 2020), it is a less cost-effective policy for increasing the quality of public servants.

Related Literature   This paper builds upon several strands of literature. It contributes to the literature of policies aimed at increasing the quality of public servants. Multiple articles study the impact of 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). With respect to recruiting policies, there is evidence on the effect of increasing salaries (Tincani, 2014, Bobba et al., 2024), incentive-based reforms (Bertrand et al., 2020, Biasi, 2021, Aneja and Xu, 2024, Muñoz and Prem, 2024, Muñoz and Otero, 2025) and entry barriers (Larsen et al., 2020, Moreira and Pérez, 2024, Dahis et al., 2025). This article contributes to the literature by studying the unexplored importance of education policies in improving recruitment. While the focus is on teachers, the results extend to other professions where the public sector is the primary employer, such as healthcare providers and social workers.

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). Additionally, it has been shown that the type of financial instrument affects major choice (Arcidiacono, 2005, Rothstein and Rouse, 2011). Beyond a partial equilibrium approach, a different strand of the literature has studied the equilibrium effects of education policies (Epple et al., 2006, Fu, 2014, Epple et al., 2017) while others have integrated education policies with the labor market in general equilibrium (Abbott et al., 2019, Khanna, 2023). Notably, there is a significant gap in the literature on the effect of policies targeted at specific degrees. Two notable exceptions are Neilson et al. (2022) and De Falco et al. (2025), who both study the same teacher recruitment policy in Chile. Neilson et al. (2022) use machine learning tools to evaluate alternative screening policies based on additional pre-college characteristics. In contrast, I build a demand and supply model to analyze optimal policy design on the basis of the status-quo covariates. De Falco et al. (2025) exploit the scholarship eligibility threshold to estimate the policy effect on enrollment using a regression discontinuity design, and assess impacts on teacher quality comparing teachers before and after the reform. My analysis extends this work in several ways. First, and with respect to enrolment, I explore heterogeneity in treatment effects and substitution patterns by income level under the observed policy. Second, I exploit the timing of the college admission process to construct a control group, enabling a difference-in-differences estimation of the policy effect on teacher quality. Third, the structural model allows me to simulate counterfactual policy rules and evaluate their effects on both enrollment composition and teacher quality, providing guidance on optimal policy design.

Finally, 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 these 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 has used the industry structure to solve 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). These studies have usually been applied in industries with a small number of firms and a clear industry leader. 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.[1]

Overview The remainder of this paper is structured as follows. Section 2 provides details of the higher education market in Chile and the stablishes the relationship between pre-college achievement and teacher effectiveness. Section 3 introduces the teacher recruitment policy and provides causal evidence of its 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 presents the estimation results. Section 7 presents the counterfactual simulations. Section 8 concludes.

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 data sources and descriptive statistics on the estimating sample, and in Section 2.3 I stablish the relationship between pre-college achievement 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 that 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 initially participated on the centralized system, while in 2012, the number increased 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, by order of preference. When applying, they have information on each program's vacancies and requirements, such as a minimum application score. Finally, given the vacancies and the rank ordered lists of both sides of the market, the centralized assignment mechanism matches students to degrees. Every degree inside the platform is required to

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[1]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).

apply a cutoff of at least 450 points. Simultaneously, students can apply for and enroll in off-platform degrees, 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).[2] The other most common instrument to finance higher education were college loans, notably a government-subsidized scheme called *Crédito con Aval del Estado*, which required a PSU average above 475 points, excluded students in the richest quintile and finances up to the full tuition amount in any accredited higher education institution.

2.2 Data

I compile information from multiple sources. Administrative records on the universe of high school and college students, scholarship applications and scholarship assignments were provided by the Chilean Ministry of Education (MINEDUC). The Department for Educational Evaluation, Measurement and Registry (DEMRE), a technical organization of the University of Chile, provided data on test score results, as well as demographic information of test takers. The National Council of Education (CNED) provided information on higher education institutions, including tuition, vacancies and admission cutoffs. Finally, the MiFuturo platform publishes detailed data on employment outcomes and wages for graduates of higher education programs across the country. It is operated by the Chilean Ministry of Education with the goal of providing prospective students with evidence-based guidance on career and study choices. My estimating sample consists of 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 affected the pool of students self-selecting into teaching degrees (Castro-Zarzur et al., 2022).

Administrative records for the universe of teachers were provided by MINEDUC. The data include information on teacher colleges, degrees, and graduation year, as well as demographic characteristics. Teachers share a unique identifier with the students' data, which allows me to link the 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

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

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. Notably, if teachers scores unsatisfactory on three occasions, they must leave the school and are 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 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 highest weight of the evaluation (60%) and is divided into two modules: In the first module, 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 the 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. Of all test takers, approximately 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 increased 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 cut-off scores, while students from higher socioeconomic status were more represented 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 more expensive) institutions entered the system in the 2012 expansion. Approximately 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 crowded in.

2.3 Pre-College Achievement and Teacher Performance

In this section I establish the relationship between pre-college achievement and teacher effectiveness. 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:[3]

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

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[4]. Because of data availability,[5] I compute mathematics teacher value added measures for 6th and 8th grade teachers, for 2013 to 2017.

Figure 1 shows the relationship between test scores at the college entrance exam and the two outcomes of teacher effectiveness under consideration. The figure shows that teachers who scored a higher score tended to perform better, as measured by their Teaching Skills and their Value Added. A simple regression indicates 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.

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[3]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).

[4]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.

[5]Standardized tests (SIMCE) were administered 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. To control for prior achievement, I estimate Value Added for 6th grade teachers in 2013, 2014 and 2015, and for 8th grade teachers in 2015 and 2017.

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.

Figure 1: College Entrance Exam and Teacher Outcomes
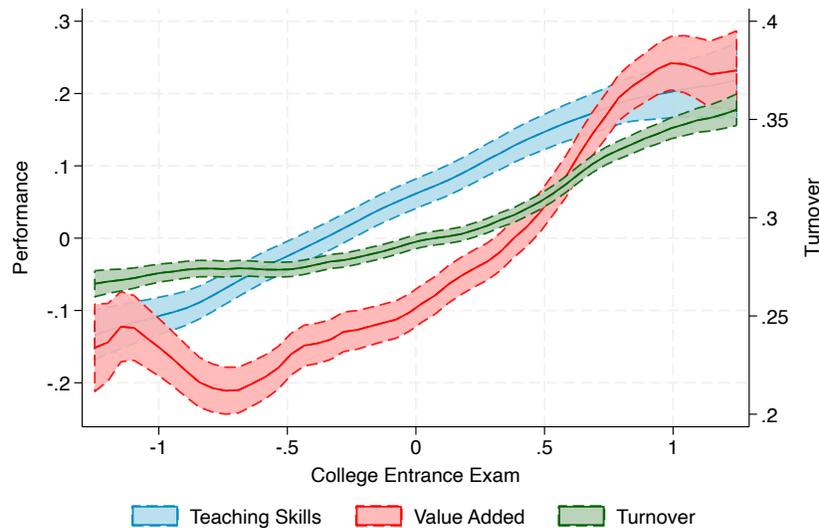
NOTES: This figure shows the relationship between test scores at the College Entrance Exam, the two measures of teacher effectiveness (Teaching Skills and Value Added) and Turnover within the first five years in the profession, by performing a kernel-weighted local polynomial smoothing. The shaded area 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   Teacher Recruitment Policy

This section provides empirical evidence on the effects of the teacher recruitment policy. Section 3.1 describes the specifics of the policy and the context at the time of implementation. In Section 3.2, I use a regression discontinuity (RD) design to show that it attracted high-achieving students to the teaching profession. Section 3.3 examines the policy's impact on labor market outcomes through a Difference-in-Differences (DID) analysis, finding that the positive composition of students at teacher colleges led to gains in average teacher effectiveness.

3.1 Context and Details

During the 2000s, education was the most popular degree of the Chilean higher education system[6]. A shortage of teachers was, therefore, not a concern. In fact, while 7-8 thousand students graduated from teacher colleges in a given year, only 4-6 thousand entered the labor market upon graduation. However, the performance of the students who were enrolled in Education degrees was substantially lower than that of students in other fields. Figure 2 shows the distribution of test scores of students enrolled in all fields, STEM degrees and teaching degrees. Students in teaching degrees scored below the universe of students pursuing a university degree, while the difference was wider than that in high-scoring fields such as STEM. Low salaries likely contribute to these findings, as teachers earn around 80% of the wage in professions with similar qualifications.[7] Additionally, 30% of all students entering an education program do so without submitting scores in the college entrance exam.

Figure 2: Test score distribution, by field of study
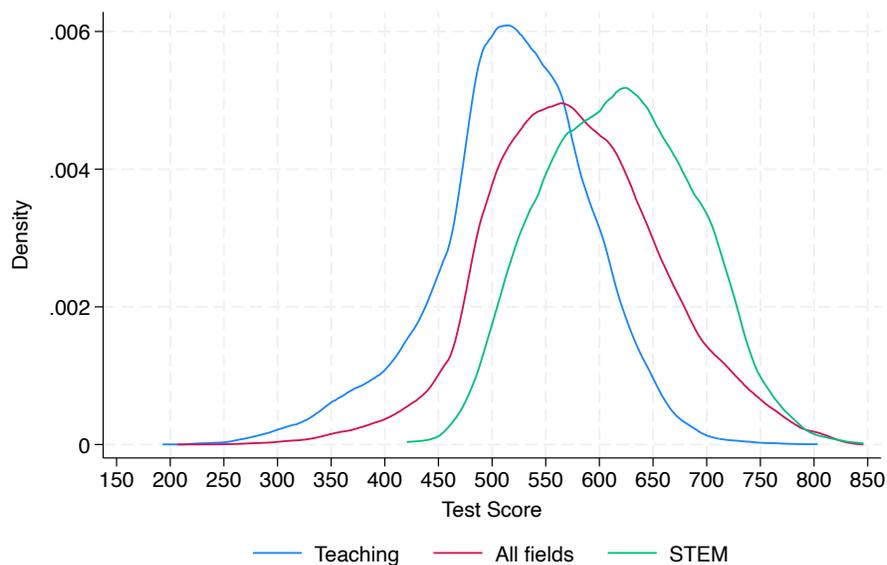
NOTES: This figure shows the distribution of test scores for students enrolled in teacher degrees, students enrolled in other fields, and students enrolled in a STEM degree, respectively, in 2010, the year before implementation of the teacher recruitment policy.

With the goal of attracting distinguished students to a career in teaching, in 2011, the Chilean Ministry of Education (MINEDUC) launched *Beca Vocación de Profesor* (BVP), a

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

[7]UIS-UNESCO, 2020.

policy that subsidizes all tuition and fees at participating teaching degrees.[8] 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).[9] Alternatively, students could qualify for the scholarship if they finish school in the highest 5% GPA of their cohort and score an average above 580 points.[10] 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 does not impose a socioeconomic requirement, that is, even students from SES-advanced backgrounds are eligible.[11]

The policy was established in public universities, while private colleges were given the option to participate. A condition was imposed on the 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 the required cutoff. However, for many universities this requirement implied a sizable reduction in enrollment, so they decided to opt out of the program. Figure 3 shows the distribution of test scores for different groups of teacher colleges in 2010 (the year before policy implementation). While for the top teacher colleges the cutoff would not have affected their enrollment (their cutoffs were already above this cutoff), those colleges with the lowest scoring students had virtually all of their enrollment below the 500 cutoff. For the median college, it was not straightforward to assume which decision would lead to higher revenues. Table A1 shows that 53% of education degrees participated in the policy upon implementation, reaching 57% by 2015. However, participation within private colleges was 30%.

The introduction of the policy implied a shift in the minimum admission score of education degrees. Figures 4a and 4b show the histogram of the cutoff scores in teaching degrees in 2010 and 2011, respectively. In 2010, a high share of degrees were located within the 450-500 points segment, but in 2011 there was a shift towards the 500-550 segment,

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[8]The policy also benefits individuals who hold a bachelor's degree (or in their last year of studies) and want to take a pedagogical complement (2 years long) to become teachers. However, I do not include them in the analysis, since they represent a negligible fraction of beneficiaries.

[9]The program also establishes a second, higher threshold of 700 points (approximately the top 5%) and students who score above it receive, in addition to all tuition and fees covered, a monthly stipend and funding for doing an exchange abroad. I do not consider this threshold in my analysis since less than 5% of beneficiaries belong to this group.

[10]In practice, fewer than 2% of scholarship holders qualified through this channel

[11]Another condition for receiving the scholarship is that, upon graduation, beneficiaries have to work at a public-financed educational establishment for 3 years. The spirit of the scholarship is not only to increase overall teacher quality but also to attract better teachers to schools where lower-SES students attend, thereby, narrowing the achievement gap (Bonomelli, 2017).

Figure 3: Test score distribution for teaching degrees
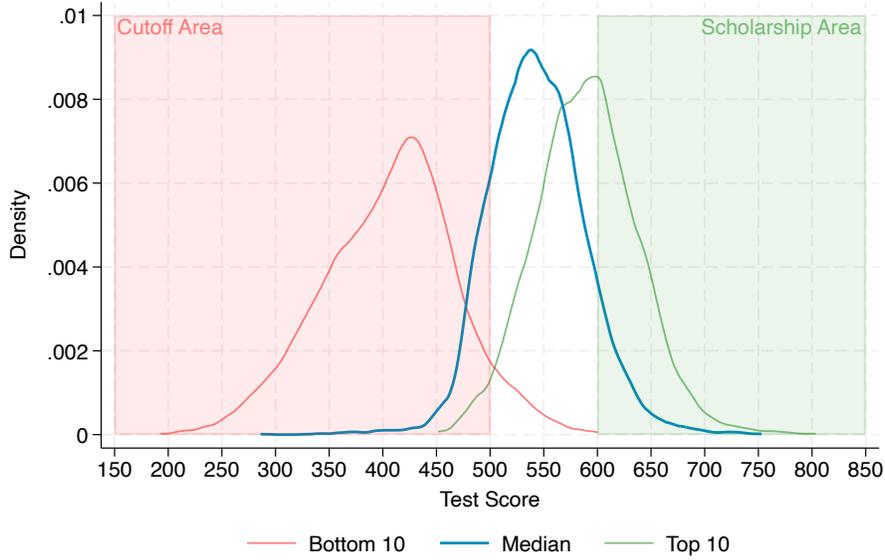
NOTES: This figure shows the distribution of test scores for the bottom 10 teaching degrees, the median program and the top 10 degrees, respectively, in the year before the policy was implemented. The ranking is based on the average test score of enrolled students.

related to the adherence of degrees to the policy. However, there was still a considerable part of the distribution below the 500 point cutoff, composed of degrees that opted out.

3.2 Enrollment Effects

I exploit the discontinuity in admissibility around the cutoff (500 points) and the discontinuity in out-of-pocket fees around the scholarship threshold (600 points), thus comparing students who scored above and below these values (within a given bandwidth). I estimate the following equation:

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

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. With respect to the scholarship threshold, it identifies the effect of scholarship eligibility on enrollment in a teacher degree. The take-up of the scholarship is above 90% for students who score above the threshold (high-performing students also enroll in non-

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Figure 4: Cutoff score at teaching degrees

(a) 2010   **(b)** 2011
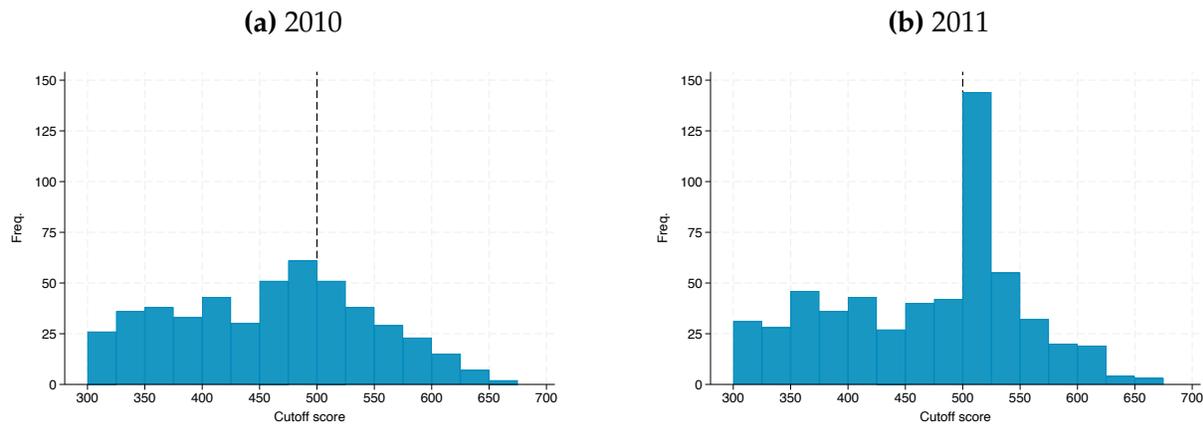
NOTES: These figures show the histograms for enrollment at teaching degrees in 2010 (Figure 4a) and 2011 (Figure 4b). A program is defined at the Institution-degree-campus level, and it includes every higher education institution.

participating degrees), and the estimate is interpreted as an intention-to-treat effect. For the cutoff, 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 whether scoring above the cutoff implies a change in take-up 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. This could have occurred because the 600 point threshold is specific to this scholarship, and students may seek to score just above this threshold to receive a scholarship. Third, eligible candidates could be systematically different in their observable characteristics.

Figure A1a 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). The take-up is zero before the 580-point threshold, and then discontinuously increases after the 600-point cutoff. Additionally, note that mean take-up after the cutoff almost exactly coincides with the mean enrollment in 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 from enrolling in a teaching degree but, conditional on enrollment, it did not dissuade them from taking a scholarship.
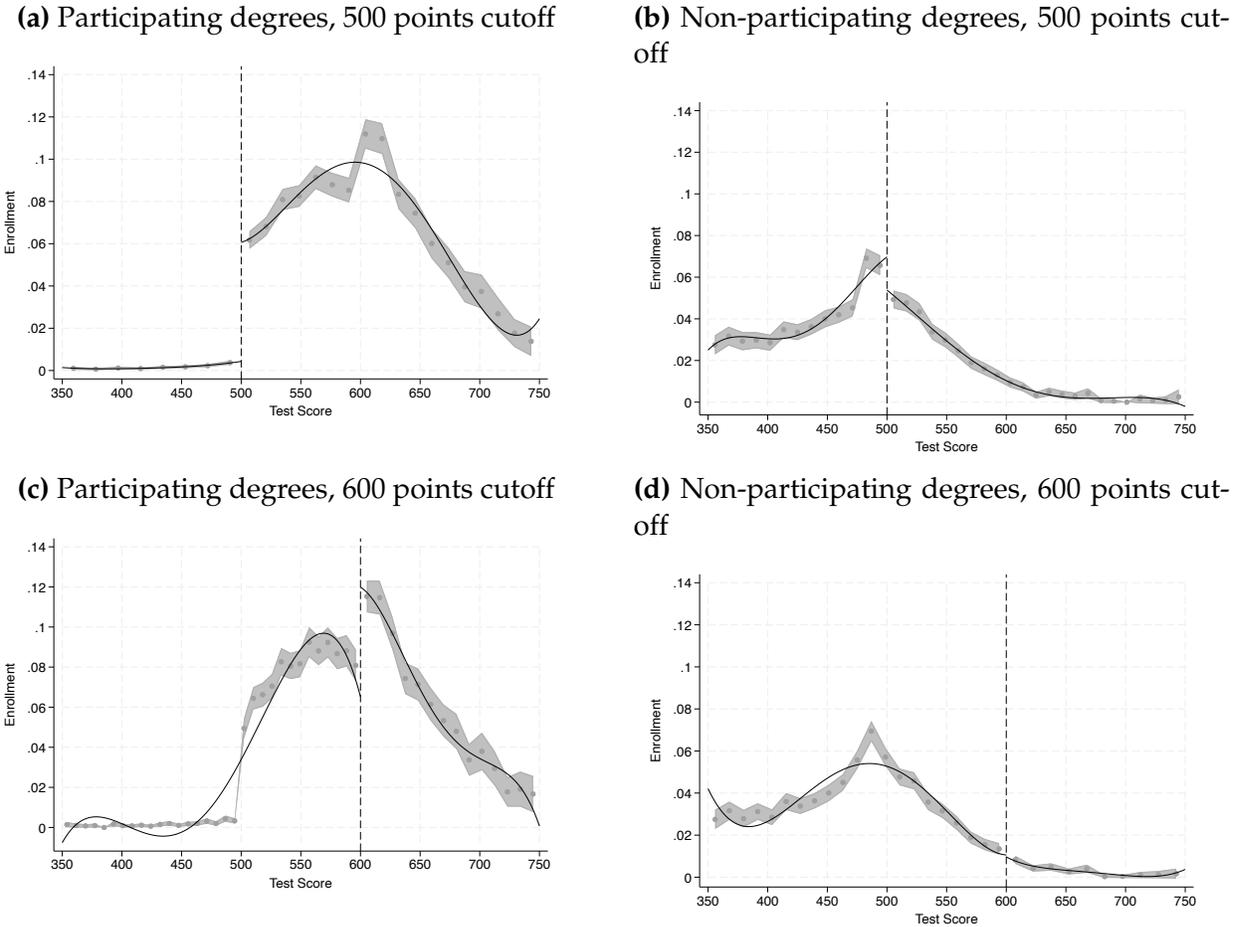
With respect to manipulation of the running variable, I perform the manipulation test of Cattaneo et al. (2020). Figure A1b shows the results of the no discontinuity around the cutoff (p-value = .829), indicating that students have no influence on their final score (besides from exerting effort). In the Chilean higher education market, it is common to retake the college entrance exam to enter a desired degree, and approximately 20% of entering students will retake the test the following year. The enrollment results could be biased if students delay their entry by retaking the exam the following year, in pursuit of scoring above the scholarship threshold. I test this by performing an RD analysis on the probability of retaking the exam the next year. Results are shown in Table A12, and the estimates show no significant effect on retaking behavior.

Table A10 shows the results 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 who enrolled in higher education, and Columns 5 and 6 show the results for every student who enrolled in a teaching degree. Results show that there are mostly no discontinuities in observable characteristics between students just below and above the 600 points threshold, within the selected bandwidth. For students whose score is 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 fields other 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 participating and non-participating teaching degrees, respectively, where the fits differ on each side of the 500-point threshold, while figures 5c and 5d do the same for the 600-point threshold. As shown in Figure 5a, for people who scored below 500, mean enrollment is zero, which constitutes evidence of the correct implementation of the policy. For non-participating degrees, Figure 5b shows that mean enrollment increases according to the test scores up until 500 points, the cutoff imposed on participating degrees. At that threshold, not only does the mean enrollment start to decrease, but a discontinuous jump in mean enrollment occurs. I relate this magnitude to students switching away from non-participating degrees to those that participate in the program. Even though the students in this score segment do not qualify for the scholarship, they enter higher quality degrees. However, considerable enrollment also occurred among people who scored above the cutoff, which suggests that students might trade off other attributes in addition to quality (such as price or geographic location) when considering enrollment.

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With respect to scholarship eligibility, Figure 5c shows that, at the 600-point threshold, there is a discontinuous jump in teacher enrollment, which highlights the effectiveness of the policy in attracting higher scoring students. Finally, there are no discontinuities at the 600 points, which is expected given that scoring above that threshold provides 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) Participating degrees, 500 points cutoff

(b) Non-participating degrees, 500 points cut-off

(c) Participating degrees, 600 points cutoff

(d) Non-participating degrees, 600 points cut-off

NOTES: These figures plot mean teacher enrollment at participating and non-participating 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-point cutoff, enrollment at participating teacher colleges increases from 0 to 5.2%. At the 600-point cutoff, there is an effect on enrollment of 3.7 percentage points.

Considering that mean enrollment below the cutoff is 8.7%, it constitutes a 42% increase in the probability of enrolling at a teacher college. In Tables A4-A9 of Appendix A 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-point threshold, the probability of enrolling in a non-participating teaching degree decreases by 1.8 percentage points, which relates to students substituting into participating degrees. Column 4 shows the null effect at the 600-point threshold for non-Participating 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 shown in Table 1. Results are shown in Table A11. The first column shows the results from the RD estimation on the 550-point threshold for the top 50% of students according to income. The biggest scholarship at that point in time, called *Beca Bicentenario*, fully covered tuition for students located in quintiles 1 and 2 of the income distribution, at any degree at an institution participating in the centralized admission system. However, richer students were not 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 for any scholarship. Columns 3 and 4 are the results for the 500- and 600-point thresholds in 2010, before the program was implemented. As expected, I do not find an effect in any case.

This enrollment result could be driven by two different application behaviors: First, students could add a teaching degree option to their ranked-order list, and end up being assigned to that option. Second, students could list a teaching degree as their top choice,

either moving up in the ranking or from not listing it at all. I test these alternative hypotheses by performing an RD analysis on both behaviors, for students who submitted ranked-order lists on the centralized platform. Results are shown in Table A13. The observed increase in enrollment in 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).

After demonstrating an 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-point 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).

Table 2 also shows that there is heterogeneity by family income on the substitution patterns. For low-income students, two-thirds of the increased enrollment in teaching degrees comes from students who have non-enrollment as their next-best alternative, while

the remainder is explained by students coming out from other bachelor's degrees. For high-income students, the increase is entirely explained by students substituting away from other bachelor's programs. Table A14 shows the results for the 500 point threshold. The substitution effect is similar for both groups of students. However, close to one-third of the substitution derives from students who have a short cycle program as their next-best alternative, whereas for high-income students all the remaining substitution is derived from non-enrollment.

Three lessons can be drawn from these results: First, the greater intention-to-treat effect reveals a greater price sensitivity for low-income students. Second, the higher baseline enrollment share for low-income students suggests that they have a greater preference for teaching degrees. Third, the different substitution patterns imply that competitive pressure to other degrees is mostly driven from high-income students. These results suggest that an alternative policy, targeted at low-income students, could prove to be more effective, and motivates the decisions to simulate a means-based policy in Section 7.

3.3 Performance Effects

The previous section revealed that the policy attracted better students to the teaching profession. In Section 2.3, I find a moderate link between pre-college achievement and teacher effectiveness. This section studies the impact that the policy had on teacher quality by performing a Differences-in-Difference (DID) analysis. 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 those 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 degrees, for cohorts before and after the policy was implemented. The identifying assumption is that the only difference for participating degrees before and after the policy is the improved pool of enrolled students, and assumes that other factors such as college quality (the contribution of a college to teacher effectiveness) remain

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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 measures of pre-college achievement as covariates. Intuitively, if the only difference is due to compositional changes, the post-policy differences should disappear after controlling for these characteristics.

Several threats to identification exist. One is due to the endogenous decision of universities to participate in the policy on a degree-by-degree basis. However, the decision to participate 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 non participating degrees that could explain the expanding gap after the policy. Figure 6a shows the trends in test scores for participating and non-participating degrees. While the test scores remained mostly constant before the policy was implemented, there was an increase in the average test scores of participating universities after policy implementation, the scores for non-participating degrees remained mostly constant for students in Non-Participating degrees. Figure A2 shows the pre-trends for test scores and teacher effectiveness measures as determined via an event study design, and results point against the existence of pre-trends.

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

I argue that the policy created a positive spillover to non-participating degrees: the influx of higher performing students to participating degrees put stress on admission thresholds, and students who did not make the new cutoffs at top institutions moved to non-participating degrees, increasing 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 support this theory: First, Figure 6a shows that the average test scores in non-participating degrees was close to 460 points, which increased slightly after the policy was implemented. Second, Figure 6b shows the distribution of test scores for participating and non-participating degrees, both in 2010 (the year prior

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to the introduction of the policy) and in 2011 (the year of policy implementation). For participating degrees, a twofold shift can be seen in the distribution: at 500 points because of the cutoff and at 600 points because of the scholarship. For non-participating degrees, the right tail remains roughly constant. However, there is variation at the 500-point area, where students are crowded out of participating degrees and move into the non-participating. These are above-average students, and the left tail of the distribution shifts to the right.

Figure 6: Test Score

(a) Time Series   **(b)** Distribution
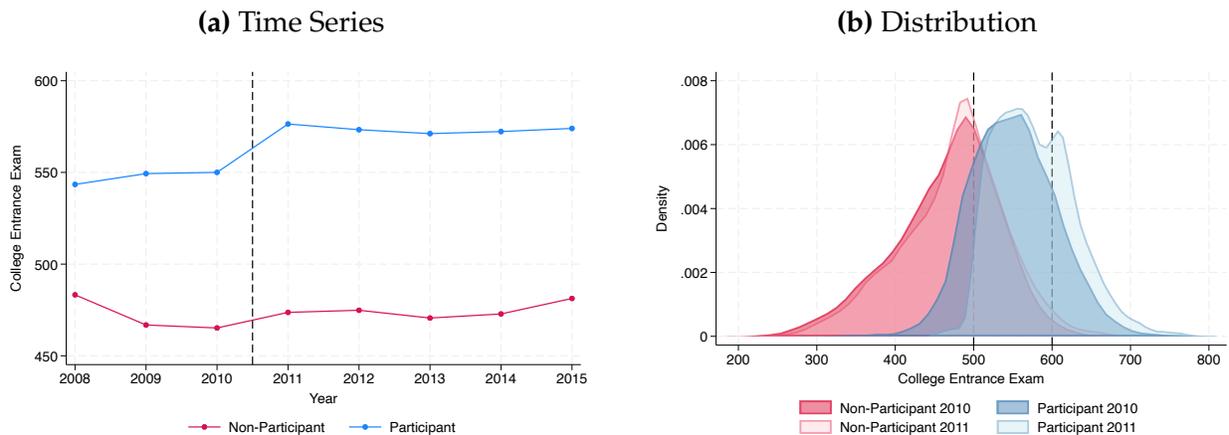
NOTES: These figures shows statistics on the average between the mathematics and language components of the College Entrance Exam. Figure 6a plots the evolution in time for test scores in Participating and Non-Participating degrees, while Figure 6b plots the distribution of test scores for Participating 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 college entrance exam as the outcome variable, for primary school teachers from 2011-2019 who belong to the 2006-2014 cohorts. I use two measures of teacher effectiveness. The first is TVA, as estimated by Equation 1. I restrict the subsample to teachers from the 2008-2012 cohorts (one year before the policy was implemented through two years after the policy was implemented).[12]

The second measure of effectiveness comes from the Teacher Evaluations Program performed by the Chilean Ministry of Education. The details are provided in section 2.2. 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 from 2006 to 2014. Test scores, TVA

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[12]The 2012 cohort is the last one for which teaching can be observed by 2017.

and teaching skills were normalized to have mean 0 and standard deviation 1; thus, the estimates are interpreted in terms of SDs.

Table 3 shows the results of the DID estimation. Column 1 shows that teachers who graduated from participating degrees had on average 0.42SD higher test scores. However, after the policy was implemented, the gap further expanded by another 0.25SD. Columns 2 to 5 show the results for 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 expected, as the most prestigious universities are the ones who participated in the policy. However, after implementation the difference increased 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 who graduated from participating degrees performed better not only because they were better students, but also because they received better training. 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 a pure-composition effect.[13]

Table 3: Estimates of Teacher Performance

	Exam	Teaching Skills		Value Added	
	(1)	(2)	(3)	(4)	(5)
Participant Degree	0.42***	0.16***	0.09***	0.12***	0.06**
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)
Post=1 × Participant Degree=1	0.25***	0.12***	0.06	0.11***	-0.00
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)
College Entrance Exam			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.
*** $p < 0.01$, ** $p < 0.05$, * $p<0.1$

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[13]Beyond the increase in test scores, De Falco et al. (2025) finds that the policy also increased the average intrinsic motivation of teachers at the left tail, as measured through a teacher survey carried out by the Ministry of Education.

Overall, the reduced-form analysis shows that the policy managed to attract high-performing students into teaching degrees. Moreover, this positive composition effect in pre-college achievement led to gains in the labor market. Appendix B explores the effects of the policy in additional outcomes, such as the turnover rate and the probability of being employed in a private school, finding null effects in both cases.

4 Equilibrium Model of Higher Education

In the previous section I showed that the policy managed to increase the quality of students at teaching degrees by attracting the higher scorers and restricting the lower scorers. This increase in high-quality students translated into better teachers upon graduation. However, my identification strategy for enrollment (RD) allowed me to estimate a local effect around an eligibility cutoff. Additionally, the identification strategy for teacher quality (DID) does not allow me to decompose the relative contribution of each policy rule. Finally, the low take-up rate for private colleges points to margins for improvement if incentives and selectivity are designed in an alternative way. To simulate market equilibrium under counterfactual policy rules, I build a demand and supply model of the higher education market, where the government sets an education policy, colleges make a joint discrete-continuous choice (policy participation and tuition setting), and students choose the college-degree combination that maximizes their utility. In addition, estimation of the value added of teaching degrees allows me to translate the changes in enrollment into teaching quality under counterfactuals.

4.1 Environment

The higher education market is characterized by a set $\mathcal{I}$ of individuals (students) and a set $\mathcal{F}$ of colleges that offer degrees contained in the set $\mathcal{J}$, such that $j \in \mathcal{J} = \{1, ..., J\}$ and $j = 0$ is 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 are related to incentives (such as grants or scholarships) and selectivity (such as cutoffs). In my application, P includes every ongoing policy, including the teacher recruitment policy, to which private universities make the strategic decision to participate.

The Chilean Higher Education Market is dual, with a subset of colleges participating in a centralized admission system,[14] whereas the rest enroll students in a decentralized

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[14]I model the centralized part of the market closely following the literature (Azevedo and Leshno, 2016,

way. I consider the centralized portion of the market and the off-platform education degrees.[15] Students have a preference order $\succ_i$ for degrees. Colleges make admission decisions solely on the basis of an index score s_{ij} that is composed of a student's multiple observable characteristics.[16] The composition of this index is degree-specific and common knowledge. Colleges might not admit every applicant into their degrees, either because they operate under capacity restrictions or they impose an index cutoff; thus, 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 (those who have not been filled by higher scoring students), and that enrollment at every degree is no greater than its capacity constraint. The matching endogenously determines a $J \times 1$ vector of score cutoffs $c(\mu)$ such that the market clears.[17] 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 $D_i(\mu) = \mu(\psi_i)$.

Abdulkadiroğlu et al., 2017)

[15]In 2011, 1020 degrees were listed on the platform. I include the education degrees 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).

[16]In practice, degrees always consider the mathematics and language components of the college entrance exam, and they can optionally put weight to the social sciences, natural sciences or other optional exam components, and students' high school GPA.

[17]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).

With the goal of targeting students to certain degrees, the government can implement alternative education 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 set of alternative rules P^* also generates a counterfactual $\succ_i^*$ as not only are the feasible choice sets altered but also the students' preference order, given a new set of equilibrium prices p^*. The preferred choice, then, can differ because of both different eligible degrees and a different ordering of them. In general, the centralized admission process generates a different matching, that is, $\phi(\psi, v) = \mu \neq \mu^* = \phi(\psi^*, v)$.

4.2 Demand

Students are utility-maximizing agents who choose a college-degree combination by trading off different attributes such as quality, distance and out-of-pocket fees.[18] A student i's indirect utility for attending program j is given by:[19]

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

where z_i and x_j are vectors of student and degrees 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 observable and unobservable characteristics of students and degrees, taking the form:

$$\begin{aligned} u_{ij} &= V_{ij} + \eta_{ij} \\ &= \delta_j + \alpha_p(1 - \lambda_{ij})p_j + \alpha_w w_{ij} + \alpha_z z_i + \alpha_q x_j z_i + \eta_{ij} \end{aligned} \tag{5}$$

The parameter δ_j includes time-invariant program characteristics (both observed and unobserved). The out-of-pocket fees faced by student i for program j depend on tuition coverage λ_{ij}, which is both student and degree specific. The utility of the outside option

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[18]While flexible enough, this framework does not account for all possible factors influencing student choices, notably the 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).

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

(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 mathematics and language components average test score, the mother's education level and an indicator variable for coming from a private high school. Match characteristics w_{ij} includes a dummy that takes a value of 1 if the student lives in a different region than the degree and the monetary value of the scholarship he's eligible for if enrolled in that degree. Degree characteristics x_j include its field and college group.[20] Individual characteristics z_i interact with both degree 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.[21] I estimate the model separately for low and high-income students, where a student is defined as low-income if his family income level is below the median, and high-income otherwise.

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

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

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.[22] Additionally, private universities make the (joint) discrete decision $B_f \in \{0, 1\}$, which determines participation in the teacher recruitment policy.[23] Without loss of generality, $B_f = 1$ is fixed for public universities. Colleges are not allowed to price-discriminate, and the effective price paid by a student depends solely on the scholarship he receives (if any). In each period, the colleges' joint profit maximization problem is given by the following equation:

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[20]Colleges are divided into four groups, defined by their private/public status and their selectivity.

[21]Details of the estimation strategy can be found in Section 5.

[22]For ease of exposition, I suppress the time subindex t in this section.

[23]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.

$$\max_{B_f, \{p_j\}_{j \in \mathcal{F}_f}} \sum_{j \in \mathcal{F}_f} \left(\Pi_j(B, p) \right) \qquad (7)$$

$$\Pi_j(p) \equiv \sum_{i \in \mathcal{I}} \left(s_{ij}(B, p_j, .) \cdot [p_j - c_j] \right) \qquad (8)$$

where c_j are the degree-specific 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 only via participation and tuition, and the discrete choice B_f affects 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.

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 an incentive to increase tuition. However, only a fraction of students are scholarship holders,[24] 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 participating degrees to variations in the consumer price index.[25]

4.4 Outcomes

The goal of the potential outcomes model is to predict the gains in teacher outcomes under a counterfactual sorting of students into degrees. I focus on two specific outcomes: teacher value added and turnover propensity.[26] I assume that the potential outcome for student i in program j has the following functional form:

$$Y_{ij} = \mu_j + X_i \beta_j + \epsilon_{ij} \qquad (9)$$

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

[25]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; thus, in general, the constraint was not binding. For counterfactuals, I fix the marginal cost of this program to the estimated value in the year before implementation of the policy.

[26]I do not use the teaching skills measure because it is observed only for teachers at public schools, which is a selected sample of below-average teachers. 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 it is correlated to preferences and observable attributes. In practice, the outcome is a dummy variable which takes a value of 1 if the individual leaves the profession within 5 years, and 0 otherwise.

The expected outcome conditional on enrollment D_i can be expressed as follows:

$$E[Y_{ij}|X_i, \Omega_i, D_i = j] = \mu_j + X_i\beta_j + E[\epsilon_{ij}|X_i, \Omega_i, D_i = j] \tag{10}$$

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 degrees on the basis of 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.[27] I proceed to follow a control function approach that links potential outcomes to preferences over degrees by conditioning potential outcomes on unobserved preferences over every degree inside a student's choice set.[28] This approach implies following the restriction:

$$E[Y_{ij}|X_i, \Omega_i, D_i = j, \eta_i] = \mu_j + X_i\beta_j + g_j(\eta_i) \tag{11}$$

where η_i, the preference shocks of student i, is a vector of size equal to Ω_i, and $g_j(\eta_i)$ is a function that flexibly controls for a student's unobserved preferences, allowing 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:

$$E[Y_{ij}|X_i, \Omega_i, D_i = j, \eta_i] = \mu_j + X_i\beta_j + \sum_{k\in\Omega_i} \omega_k \, \eta_{ik} + \varphi \, \eta_{ij} \tag{12}$$

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 for an elite engineering program is more likely to be a high ability student (beyond what is captured in test scores), implying that he will have a higher potential outcome even if he enrolls 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.

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[27] As noted 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.

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

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 prefer 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) showed that the equilibrium is unique and that the mapping is continuous, and Fack et al. (2019) demonstrated that, as the number of students grow, the matching game converges to a discrete choice model with personalized choice sets.[29]

On the supply side, colleges make a continuous choice (price) for every program they offer, and the (joint) discrete choice of policy participation. 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 55 colleges offer a teaching degree, and computing 2^{55} market structures is computationally infeasible (for both the players and the econometrician). Therefore, I depart from standard equilibrium theory and assume that 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 payoff, 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 is best for them given their beliefs. However, mutual consistency does not hold, as they may have mistaken beliefs about the 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 degree j offered by college f, compute $\partial s_j / \partial p_k$ for every education degree of another college.

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[29]Specifically, as the number of students grows large, the percentage of students who receive a stable matching outcome converges to 1 in probability.

2. Order the degrees by $\partial s_j / \partial p_k$.

3. The close rivals of college f are the colleges who offer the k degrees with the highest $\partial s_j / \partial p_k$.

Therefore, the notion of being a "rival" includes only players who participate in the discrete decision (private colleges that offer an education degree), while every program is considered while making the continuous choice (prices). Note that rivalry 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 (Figure 7a), where every player has an industry leader as a close rival, and a segmented industry (Figure 7b), where players tend to compete in clusters.

Figure 7: Equilibrium in Close Rivals

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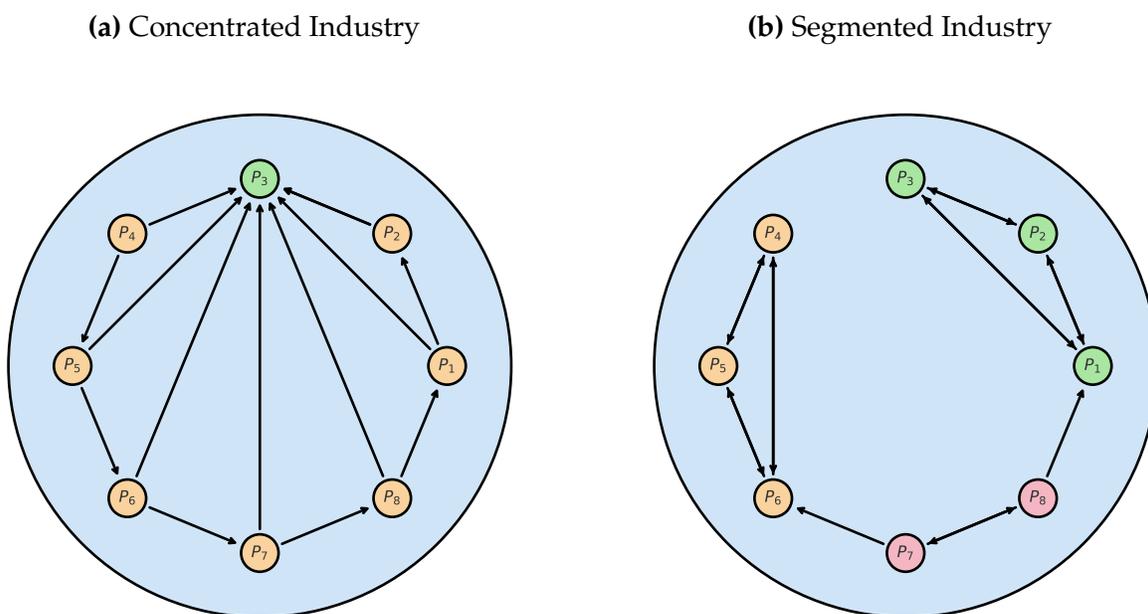
NOTES: These figure shows examples of competition in different type of industries, for the case of 2 close rivals. Figure 7a shows a concentrated industry, where every player tracks an industry leader and a close rival. Figure 7b shows a segmented industry, where close rivals tend to form clusters.

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. In Section 5.4 I describe the criterion function to select the number of close rivals that colleges account for when they make their decisions. Section C.1 from the Appendix describes a series of simulations to assess the performance of bounded rational colleges in approximating a Nash Equi-

librium, while Appendix E describes the procedure for solving for an equilibrium when simulating counterfactual policy rules.

5 Estimation

In this section, I discuss the identification of the model and the estimation strategy. The estimation is performed 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. The estimates from the demand model also allow me to compute the conditional expectation of 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 models, I estimate the number of close rivals k that colleges consider when they make their decisions.

5.1 Demand

I estimate the demand model following the method for differentiated product 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 college entrance 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. The model is estimated with data on realized matches, while the outside option is to not enroll in any program.

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

$$\mathcal{L}(\alpha, \delta) = \sum_{i=1}^{n} \sum_{j \in \Omega_i} d_{ij} \log \mathrm{P}\left(\mu_i^* = j \mid z_i, x_j, w_{ij}, \Omega_i \; ; \; \alpha, \delta\right), \quad d_{ij} = \mathbb{1}\{\mu_i^* = j\} \tag{13}$$

where the probability of observing the matching μ_i^* depends on the characteristics of students and degrees, the students' feasible choice sets and the parameters to estimate. The

procedure, therefore, searches for the parameters that generate the students' preference ordering 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:

$$\mathcal{S}_j = s_j(\alpha, \delta_j(\alpha)) \quad \forall j \in \mathcal{J} \tag{14}$$

$$s_j(\alpha, \delta) \equiv \mathcal{I}^{-1} \sum_{\mathcal{I}} \mathbb{1}\{\mu_i(\alpha, \delta) = j\} \tag{15}$$

I use the nested fixed point algorithm of Berry et al. (1995).[30] The inner loop, therefore, solves for the mean utilities δ_j that (for given α) make Equation 14 hold, whereas the outer loop minimizes the log-likelihood function in Equation 13, for a given vector of δ, by searching for the preference parameters α. The estimation is performed separately for low and high-income students; thus, every parameter can vary across these two groups.

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 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:

$$\alpha_p = \frac{1}{L} \sum_{l=1}^{L} \left(\pi_l \frac{1}{J} \sum_{j \in \mathbb{J}} \frac{\lim_{r \to \bar{r}^+} \log \frac{s_{rlj}}{s_{rl0}} - \lim_{r \to \bar{r}^-} \log \frac{s_{rlj}}{s_{rl0}}}{p_j} \right) \tag{16}$$

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[30]The algorithm was originally developed for the case where every product in a given market would be in the choice set of every individual. Figure A4 compares the estimation based on the full choice set and the feasible choice set, generating virtually the same distribution of δ_j, up to a scale difference.

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

where π_l is 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 D 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 D provides further details on the identified parameter in a simplified model, and in Section 6.2, I show that the estimated parameters can successfully replicate the discontinuities found in the data.

5.2 Supply

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

$$S^f + \Delta^f (P^f - C^f) = 0 \tag{17}$$

where $\Delta_{jk}^f = \frac{\partial s_k}{\partial p_j}$ 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 17 for the observed market shares and prices. They depend on the estimation of the demand parameters α (to compute the cross-price elasticities of demand Δ_{jk}^f); therefore, the estimation is performed sequentially.

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:

$$Y_i = \mu_j + X_i \beta_j + \sum_{k \in \Omega_i} \omega_k \, \lambda_k(X_i, \Omega_i, D_i = j) + \varphi \, \lambda_j(X_i, \Omega_i, D_i = j) + \epsilon_i \tag{18}$$

The control function $\lambda_j(X_i, \Omega_i, D_i = j) = E[\eta_{ij}|X_i, \Omega_i, D_i = j]$ is the mean logit preference for program j, conditional on observable characteristics, the feasible choice set and the

enrollment decisions. These expressions have a closed-form solution and can be directly estimated from the data.

Estimation of Equation 18 yields estimates of value added parameters for each degree $\theta_j = (\hat{\mu}_j, \hat{\beta}_j)$, with the associated control function parameter $\hat{\omega}_j$. While unbiased, they are noisy estimates of the true parameters. To reduce the sampling variance, I perform a hierarchical empirical Bayes shrinkage, following Walters (2024).[32] I consider θ_j to be a random draw from a mixing distribution, and define the hyperparameters χ_θ and Σ_θ as its mean and variance, respectively. I estimate χ_θ as the average over all $\hat{\theta}_j$, while the estimator for the variance is as follows:

$$\hat{\Sigma}_\theta = \frac{1}{J} \sum_{j=1}^{J} (\hat{\theta}_j - \hat{\chi}_\theta)(\hat{\theta}_j - \hat{\chi}_\theta)' - \hat{\Upsilon}_j \tag{19}$$

where Υ_j is the sampling covariance matrix of $\hat{\theta}_j$. Walters (2024) shows that removing the excess variance due to sampling error yields a consistent estimator of Σ_θ. The posterior predictions take the following form:

$$\theta_j^* = (\hat{\Upsilon}_j^{-1} + \hat{\Sigma}_\theta^{-1})^{-1}(\hat{\Upsilon}_j^{-1}\hat{\theta}_j + \hat{\Sigma}_\theta^{-1}\hat{\chi}_\theta) \tag{20}$$

I use the empirical Bayes predictions to compute treatment effects under counterfactual policies. One of the outcomes under consideration is teacher value added, which is estimated in a previous step following Equation 1, with all the teachers with available information. When I plug the estimates into the left-hand side of Equation 18, I use the unshrunk estimates, as the shrinkage on the dependent variable would introduce non-classical measurement error, thereby generating bias.

5.4 Equilibrium Selection

Close rivals are determined by the estimated $\hat{\Delta}$ from Equation 17, 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

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

method that combines the structural model with market data. The number of close rivals considered by players is that which minimizes the following criterion function:

$$\underset{k \in \{0,..,N\}}{\arg \min} Q = \sum_N \sum_{j \in \mathcal{F}_f} \left(\hat{\Pi}_j(k) - \hat{\Pi}_j^* \right)^2 \tag{21}$$

where $\hat{\Pi}_j^*$ is the estimated profit of program j under the observed market conditions, and $\hat{\Pi}_j(k)$ is the estimated profit assuming that 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 that they have perfect information about the 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 do not offer an education program are not considered, as they do not take any discrete choice. The deviation boils down the model fit to 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 of the demand estimation can be found in Table A15, and the distribution of marginal costs and markups are shown in Figure A3. Several features should 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 socioeconomic status (in the model, reflected by a binary variable for having attended a private high school). Students with higher test scores have a greater preference for elite colleges, while students who attended a private high school

have a greater preference for a subgroup of private colleges, which are higher quality than the average public college, and are 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 greater preference for most fields, the estimated difference for education degrees tends to be negative, which indicates that low-income students tend to have a greater preference for education degrees than high-income students do. Combined with a higher disutility for prices, this implies that low-income students are more likely to enroll in education degrees than high-income students are, which is consistent with the observed enrollment patterns.

Figure 8: Difference in Mean Utilities for High and Low-Income Students
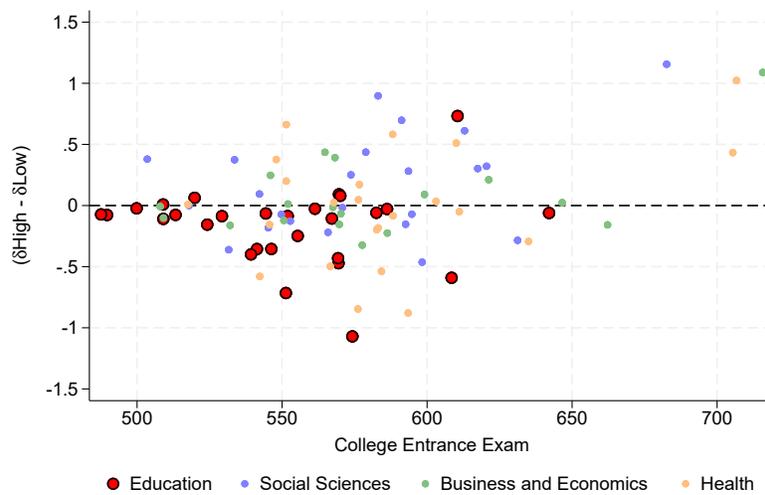
NOTES: This figure plots the difference in (standardized) mean utilities between High and Low-Income students. The x-axis corresponds to the program's selectivity (in terms of the average tests scores at the College Entrance Exam), while the y axis corresponds to the difference in mean utilities ($\delta_j^{\text{High}} - \delta_j^{\text{Low}}$). The degrees 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 degrees' 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, as students apply to both in and off platform degrees, and aftermarket frictions are substantial (Kapor et al., 2024). Additionally, to ease the computational burden, I collapsed multiple degrees into a unique college-field option.

The model can also successfully replicate the discontinuities generated by the admission

Figure 9: Model Fit - Demand Estimation

(a) Market Shares

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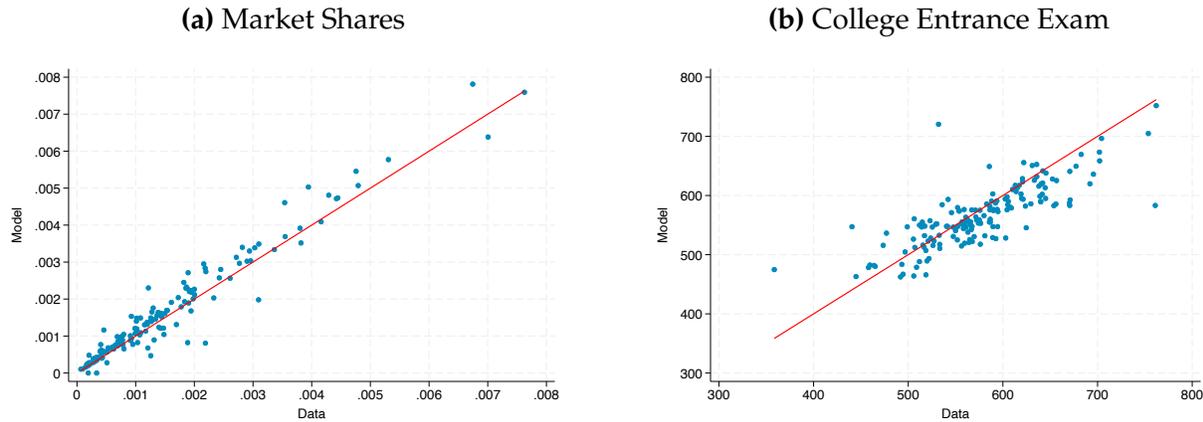
NOTES: These figures show the results for the model fit of the demand estimation. The x-axis corresponds to observed values, while the y-axis corresponds to predicted values. The dashed line shows the 45 degree line. In each plot, a point corresponds to the average value for a given program.

and scholarship rules (the 500- and 600-point thresholds, respectively), as shown in Figure 10, which plots the enrollment probabilities for teaching degrees.

Figure 11 shows the model fit for the potential outcomes model. To minimize the risk of overfitting, I estimate Equation 18 including, for each individual, the control function parameters corresponding to the chosen option and the five non-chosen options with the highest estimated utility within each student's feasible choice set. Intuitively, any option further away provides less additional information about the unobserved preferences that determine selection. In Figure A5 and Figure A6, I report the model fit for a varying number of control function parameters. While including the control functions improves the fit, the gains quickly diminish with respect to the number of parameters. After a given threshold, any additional parameter effectively worsens the correlation between the estimated teacher value added and the prediction based on the control function approach.

Figure 11a shows that the OLS model does a poor job of 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 0.39, whereas the correlation with respect to the control function prediction is 0.79. Figure 11b shows that the control function approach does a good job in predicting the average turnover of education degrees. At the program level, the correlation between observed turnover and the OLS prediction is 0.74, whereas the correlation with respect to the control function prediction is 0.86.

Figure 10: Model Fit - Enrollment in Teaching Degrees
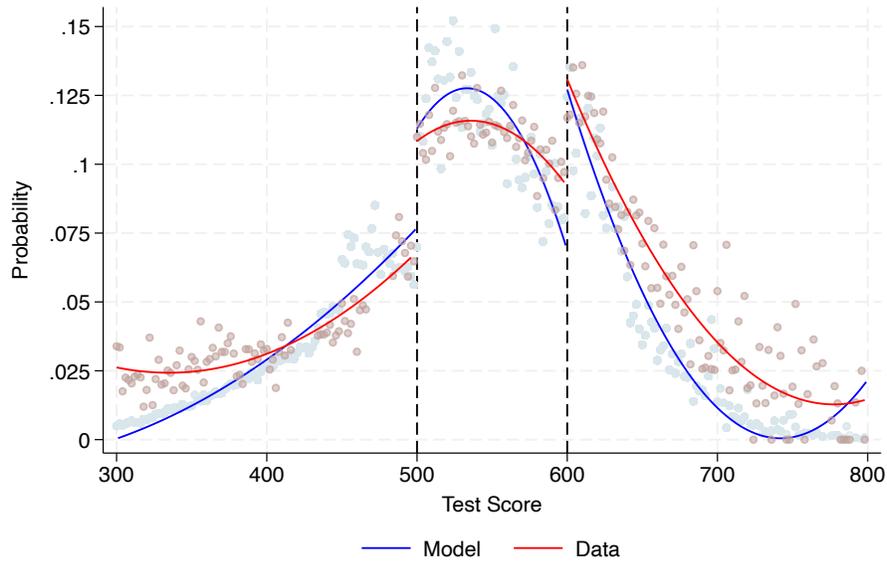
NOTES: This figure shows the enrollment probabilities in Teaching Degrees. The x-axis corresponds to the College Entrance Exam score, while the y-axis corresponds to average probability of enrollment at a Teaching Degree. The dashed lines correspond to the admission rule (500 points) and the scholarship 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.

6.3 Equilibrium Selection

Figure 12 shows the results of estimating Equation 21 for different values of k. First, note that the criterion function is U-shaped, and the minimum is reached for $k = 4$. This finding 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 than the data show. This notion, therefore, better captures the heuristic behavior of colleges. In particular, it captures the fact that degrees 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. As 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.

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 presents the results of the policy

Figure 11: Model Fit - Outcomes

(a) Teacher Value Added

(b) Turnover
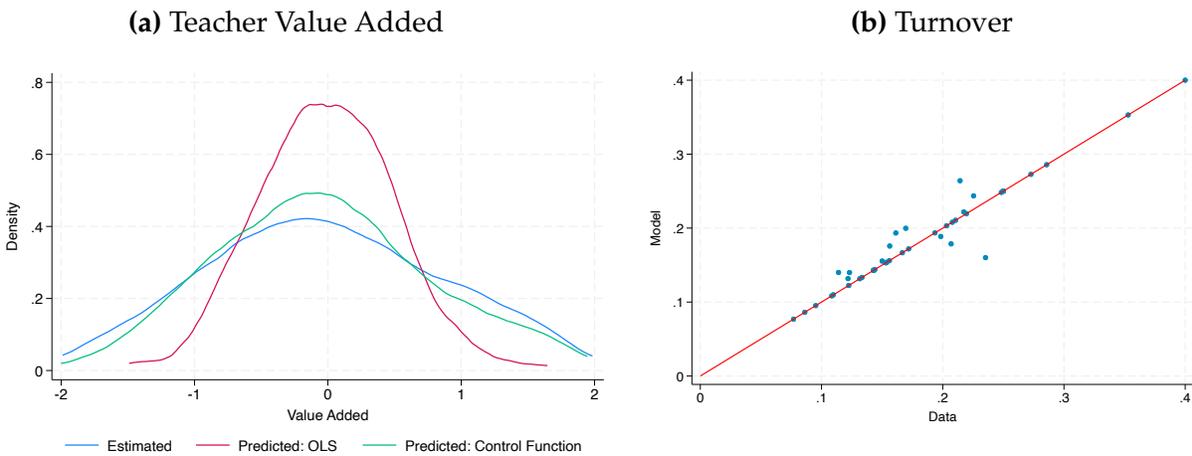
NOTES: These figures show the model fit for estimating Equation 18, as well as an OLS specification that does not control for unobserved heterogeneity. Figure 11a shows the distribution for (a) the estimated Teacher Value Added for students who enrolled in an Education program and later worked as teachers, (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.

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 scholarships are only offered to low-income students. Finally, to compare the effectiveness of an education policy versus an alternative intervention, Section 7.4 simulates a policy that increases the wage of graduates from teaching degrees.[33]

7.1   Decomposing the Policy

To study the effect of each individual component in isolation, I first simulate counterfactual scenarios where I vary one of the components in isolation. Note that, to generate variation in participation, both components need to be present: in the absence of a cutoff rule, every program weakly prefers to participate in the policy, and in the absence of a scholarship rule, every program weakly prefers to opt out. Therefore, I proceed to fix in each case the rule at 400 points, which generates sufficient variation in both the colleges' and the students' decisions.[34]

The results can be found in Figures 13, 14 and 15. The first figure shows the decision to

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[33]Appendix E explains the steps for simulating counterfactual policy rules.
[34]For the cutoff counterfactuals, the scholarship rule is effectively at the cutoff.

Figure 12: Criterion Function
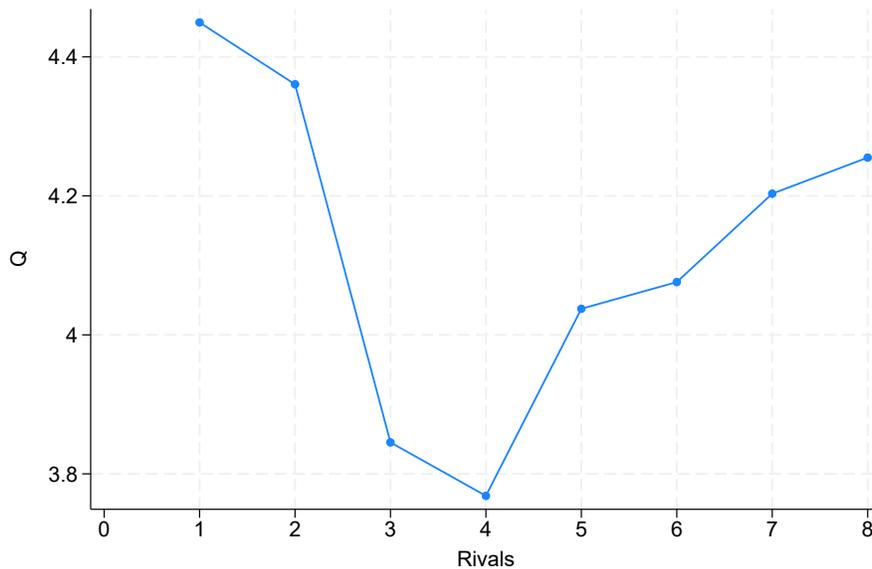
NOTES: These figure shows the results for the Criterion function for selecting the number of optimal close rivals. The x-axis shows the number of close rivals, while the y-axis shows the value of the criterion function. The dashed line shows the value of the criterion function for the observed data.

participate of all colleges who offer an education degree, under the counterfactual cutoff (Figure 13a) and scholarship (Figure 13b) threshold rules. For the cutoff counterfactuals, participation drops sharply, and no program chooses to freely participate for values above 550 points, where only public universities participate. As I do not model exit, I assume that degrees in public colleges will remain despite that for implausible high cutoff values they would lose virtually all their enrollment. Therefore, these Figures serve to delineate the region of plausible policy rules. For the scholarship value, however, the effect is more gradual. As the scholarship rule increases, the lowest quality degrees are the first to opt out, as they fail to attract enough students to compensate for those that they lose because of the cutoff. For a scholarship rule of 600 points, some high-quality private universities still opt-in, as they have sufficiently high cutoff scores.

Figure 14 shows the effect of the policy on the market shares of education degrees. Figure 14a shows the effect of varying the cutoff while keeping the scholarship threshold constant, whereas Figure 14b shows the effect of varying the scholarship threshold while keeping the cutoff constant. As seen in Figure 14a, private colleges preserve mostly a constant market share, as they quickly opt out from the policy, and do not succeed in capturing students from other fields. The public colleges remain in the policy by design, and therefore lose market share. For a sufficiently high cutoff, their market share drops

Figure 13: Simulated Participation

(a) Alternative Cutoff Rules

Note: Scholarship threshold is 500

(b) Alternative Scholarship Rules

Note: Cutoff threshold is 450
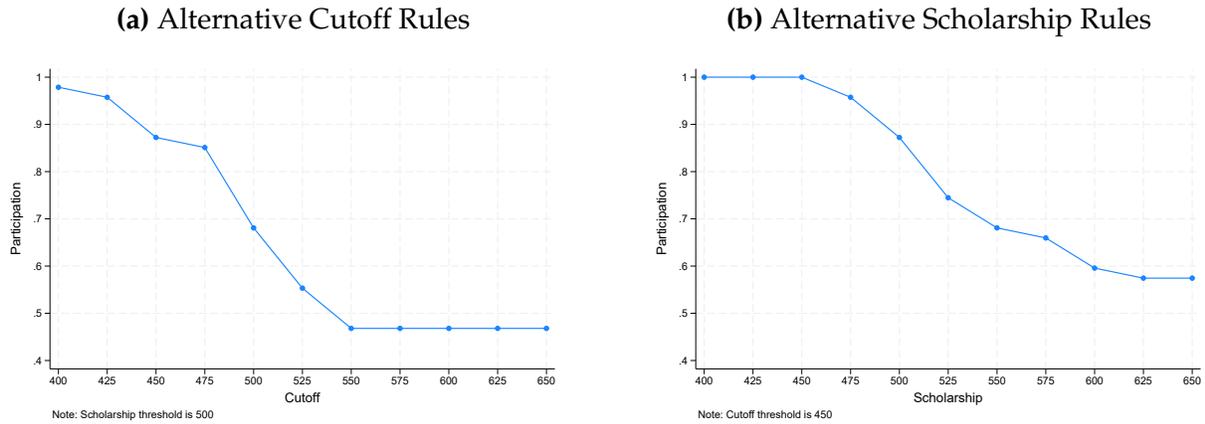
NOTES: These figures show the participation decision of Education degrees under counterfactual policy rules. Figure 13a shows the effect of varying the cutoff while keeping the scholarship threshold constant, while Figure 13b shows the effect of varying the scholarship threshold while keeping the cutoff constant.

virtually to zero, and the market share of all education degrees converges to the one of private colleges. From Figure 13b it can be seen that the decrease of market shares is less severe, as the high-quality degrees are able to retain most of their students, while failing to attract new ones for the high scholarship thresholds.

Figure 14: Simulated Market Shares

(a) Alternative Cutoff Rules

Note: Scholarship threshold is 600

(b) Alternative Scholarship Rules

Note: Cutoff threshold is 450
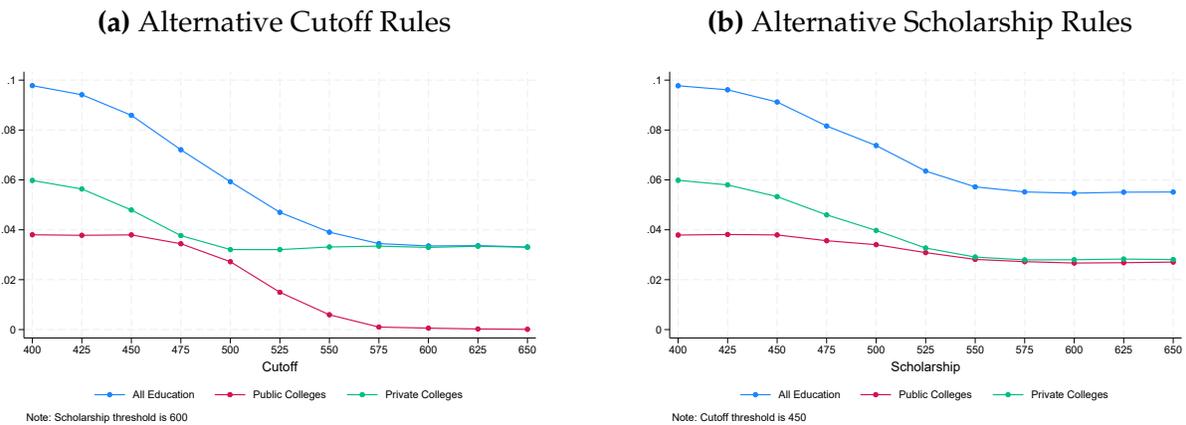
NOTES: These figures show the market shares of different set of degrees under counterfactual policy rules. Figure 13a shows the effect of varying the cutoff while keeping the scholarship threshold constant, while Figure 13b shows the effect of varying the scholarship threshold while keeping the cutoff constant.

Figure 15 shows the average test scores of education degrees under the counterfactual policy rules. As shown in Figure 15a, the average test scores for public universities increase sharply with the cutoff, as participation in the policy is fixed by design. However, as their market share simultaneously sharply declines, test scores first increase (due to

a positive composition effect) but then decrease and converge to those 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), whereas the decrease coincides with private colleges opting-out of the policy, since they fail to attract students with high enough scores. Public colleges, however, are able to retain most of their students; therefore, their average test scores remain mostly constant.

Figure 15: Simulated Test Scores

(a) Alternative Cutoff Rules

(b) Alternative Scholarship Rules
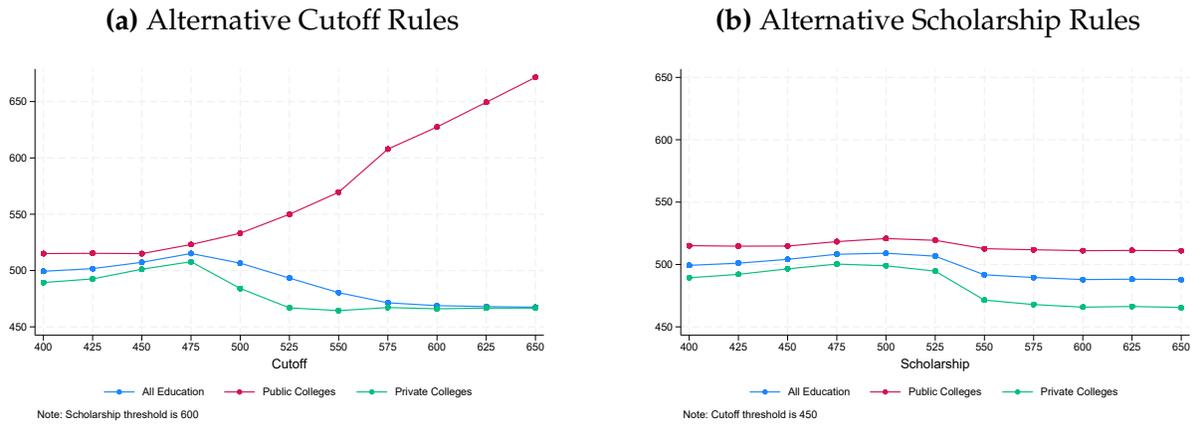

NOTES: These figures show the average test scores of Education degrees under counterfactual policy rules. Figure 13a shows the effect of varying the cutoff while keeping the scholarship threshold constant, while Figure 13b shows the effect of varying the scholarship threshold while keeping the cutoff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

7.2 Optimal Policy

While Figures 13, 14 and 15 are useful for analysing the effect of each individual component in isolation, there might be potential gains on the interaction of both components. I simulate a grid of counterfactual policy rules, which can be found in Figure 17. I omit simulations for scholarship parameters below cutoff parameters, as they generate the same equilibrium as in the case in which they are equal.

Figure 16: Simulated Colleges' Responses
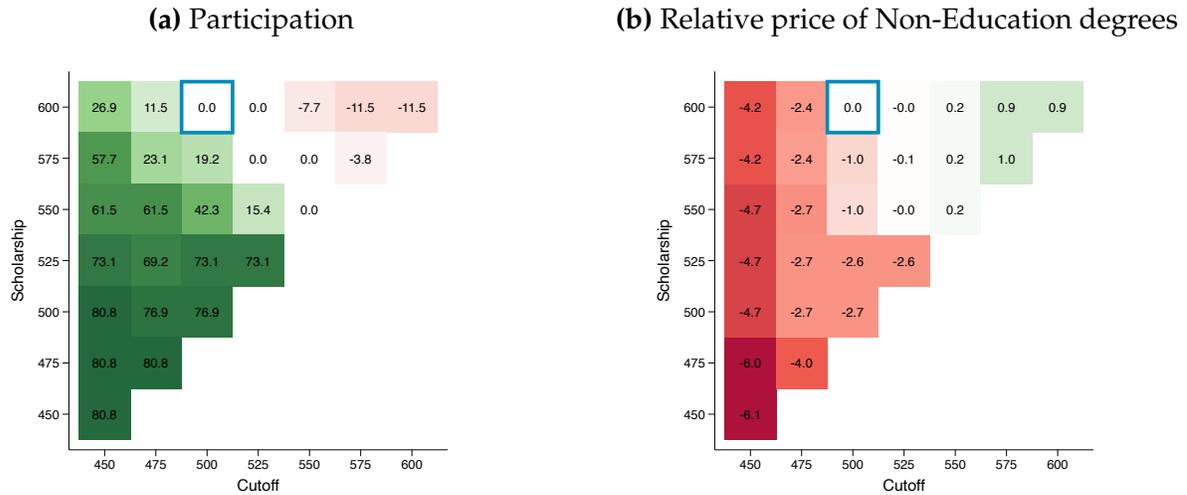
(a) Participation

(b) Relative price of Non-Education degrees

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. Figure 16a shows the difference in participation rates, while Figure 16b shows the difference in the relative price of Non-Education degrees, with respect to Education degrees, as computed by $\bar{P}(\text{Non-Educ})/\bar{P}(\text{Educ})$.

Figure 16a shows that participation varies dramatically across policy configuration, as almost all education degrees opt-in for low cutoff-scholarship combinations, whereas for a considerable region, only public colleges participate. Therefore, a more lenient policy, in the sense of a lower admission standard- combined with more generous funding- by lowering the scholarship threshold, tends to magnify the impact of the policy via increased take-up of private colleges. However, the policy leads to a demand shock for education degrees, and colleges might adjust more than their participation margin. Figure 16b shows that the relative price of non-education degrees decreases as the policy is expanded. This is because colleges have limited capacity to absorb the demand with their own education degree. Once at full capacity, they might lose enrollment from their other degrees, as students seek an education degree elsewhere. This reaction tends to attenuate the expansion. This highlights the importance of accounting for both margins of adjustment: simulations that keep either participation or tuition fixed would lead to biased estimates of the policy impact.

Figure 17 shows the aggregate market shares, public spending and entrance exam scores at teaching programs under counterfactuals. Figure 17a shows that market shares find their maximum for the lowest combination of cutoff and scholarship parameters, and their minimum for the highest cutoff-scholarship combination. Test scores are non-monotonic, as shown in Figure 17c. There are potential gains from decreasing the cutoff and scholarship rules. For example, if the cutoff is lowered to 450 points, the maximum test score

gains will be at a scholarship threshold of 525 points. For scholarship parameters below that point, degrees effectively attract below-average students, whereas for higher scholarship parameters, many colleges start to opt-out, as they fail to attract enough good students to compensate for the lost enrollment, and the students that they do attract do not offset the below-average students drawn by the low cutoff.

Figure 17: Simulated Market

(a) Market Shares   **(b)** Public Spending   **(c)** Entrance Exam Scores
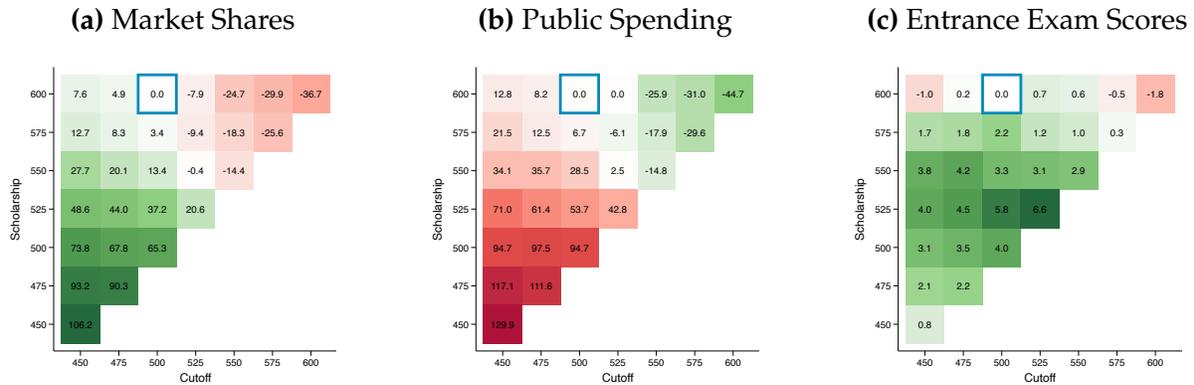

NOTES: This figure shows the results of counterfactual simulations under a grid of policy parameters. In all cases, the value is the percentage difference with respect to the observed policy. Figure 17a shows the difference in market shares of Education degrees, Figure 17b shows the difference in the total amount of public spending and Figure17c shows the difference in average test scores at Education degrees.

Compared to the observed policy, the combination implies an increase both in the average test scores and in market shares. However, as shown in Figure 17b, this configuration is dramatically costlier, as most of the students pursuing an education degree would have a full scholarship; therefore, the policymaker should trade off quantity, quality and cost when determining the optimal policy. Moreover, maximum gains are observed 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 18, several things are worth noticing. First, as shown in Figure 18a, the pattern for value added does not follow that for test scores. An explanation of this feature can be rationalized by Figure A7. This figure shows the distribution of degree value added, which are the fixed effects recovered when Equation 18 is estimated with teacher value added as the dependent variable. The increase in the market share of education degrees that results from lowering the cutoff is driven by those degrees who have spare capacity in the baseline, which are the lowest quality degrees. While most degrees have a close to null value added, there is a subset of degrees with a negative estimated value added, and increasing the market share of those

degrees, even though it increases the average test scores of students enrolled in education degrees, implies a negative composition effect on teacher effectiveness.[35] Increasing the average teacher value added can be achieved only with a strict cutoff rule. However, Figure 18b reveals that reduced market shares is not the only cost to pay: the predicted turnover for those students enrolled in education degrees will be higher. This is consistent with the literature, as high-ability teachers are not rewarded by their performance in class, while they have a higher value for their outside option.[36]

Figure 18: Simulated Outcomes

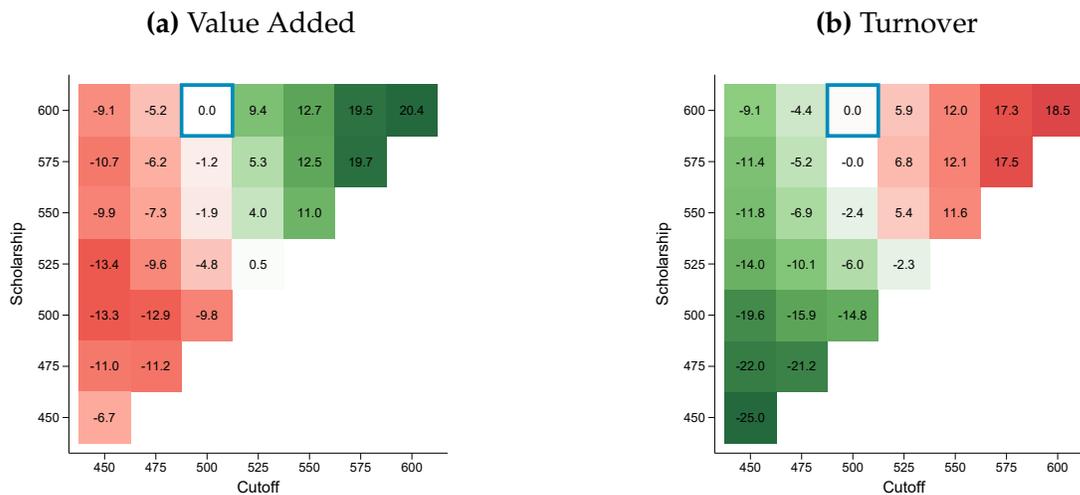**(a)** Value Added

(b) Turnover

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. Figure 18a shows the difference in teacher value added and Figure 18b the difference in turnover rates, which results by estimating Equation 18.

7.3 Means-Based Policy

There are multiple reasons why implementing a means-based policy is desirable not only for equity concerns but also for efficiency. First, the results from Table 2 show that the effect on enrollment for low-income students is double the effect for high-income students. This is consistent with the results from the demand estimation (found in Table A15), which show that low-income students have a greater preference for education degrees (Figure 8) and are three times more price sensitive, making them more likely to

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

[36]Tartova (2025) finds that high-productivity teachers are 2.5 times more responsive to wage increases in their exit decisions than low-productivity teachers.

switching 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 entirely drawn from other fields. This means that targeting low-income students would put less competitive pressure on other fields, which has been shown to affect pricing decisions. Third, among the share of low-income students who 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 A8, where each cell shows the percentage difference with respect to the observed (non-means-based) policy. First note that a means-based policy under the observed cutoff-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 from implementing a means-based policy. For example, instead of implementing a non-means-based policy in the rules $\{575; 575\}$, which implies a reduction of 25.6% in enrollment, a 19.6% increase in value added and a 17.5% increase in Turnover, a means-based policy in the same rule implies a reduction of 23.7% in enrollment, a 14.9% increase in value added and a 16.2% increase in turnover. Several other combinations also achieve efficiency gains. However, it is worth noting that maximum value added gains (20.4%) are achieved for a non-means-based policy, as it implies the best possible composition of students on public and elite private colleges.

7.4 Wage Policy

The model can also be used to analyze the effect of a policy that is not based on scholarships or admission rules. The most popular of these policies is wage increases. I consider a policy that increases the wages of graduates from education degrees, and focus on the effect on recruitment, as my model does not allow me to estimate on-the-job responses. However, the literature has found that neither wage increases (de Ree et al., 2018) nor wage decreases (Bau & Das, 2020) impact the performance of incumbent teachers, with the gains being driven by changes in the pool of candidates (Tincani, 2021, Bobba et al., 2024). I recover preferences for wages by regressing the mean preference parameters δ_j with data on wages at the college-major level, four years after graduation. I simulate alternative policies that increase the average wage of graduates from education degrees by different magnitudes.

Results of the wage policy can be found in Table 4. The increase in wages generates a positive demand shock for education degrees, which increases their market shares. In terms of test scores at the entrance exam, the increases are weak, as colleges do not have incentives to increase their admission standards. To achieve the same gain in test scores as the best education policy, the government would need to increase wages by approximately 35%. However, the observed oversupply of students at teacher colleges would be amplified, as such a policy would increase the market share of education degrees by 66%.

Table 4: Wage policy

(1) Increase (%)	(2) Market Shares	(3) Entrance Exam	(4) Value Added	(5) Public Spending
5	10.76	0.84	-0.91	0.66
10	22.66	1.51	2.38	4.81
15	31.62	2.74	3.47	7.99
20	39.08	3.90	8.11	8.64
25	48.23	4.91	13.07	14.81
30	56.98	5.62	18.52	15.21
35	66.21	6.36	26.37	19.84
40	75.56	7.14	35.92	27.59
45	82.69	8.10	44.32	39.68
50	89.71	8.88	57.34	41.99

NOTES: This table shows the estimates simulating alternative policies that increase the wage of graduates from teacher colleges. Column 1 shows the percentage increase in wages, while columns 2-5 show the percentage difference with respect to the baseline. Column 5 refers to the increase in public spending in higher education (due to scholarships), not taking into account the increase in public spending due to higher wages.

In addition, the increase in the total amount that the government spends on scholarships would be similar: even in the absence of the teacher college scholarship, students qualify for other types of means-based and merit-based scholarships, and the government would increase its spending approximately 20% with respect to the observed policy. This increase in spending does not take into account the increase in public spending due to the increase in the wages of every public school teacher, which would be orders of magnitude greater.

Overall, implementing a wage policy for improving recruiting appears as a less efficient way of using public funds, as it would increase the oversupply of teachers, while achieving lower gains in test scores and at a similar fiscal cost.

8 Conclusion

This paper studies the design of higher education policies targeted at improving the recruitment of public servants. I present a framework for the types of policies upon consideration, which are based on two instruments the government can set: (i) an eligibility rule for public funding, in the form of a scholarship, and (ii) an admission rule that restricts students from enrolling in certain degrees. I present a case within that framework, a policy launched in Chile that aims to increase teacher quality by crowding in high performing students to Education degrees, while crowding out low performing students. I present causal evidence that the policy managed to increase the enrollment of high performing students in teaching degrees. Moreover, this increase in the composition of students sorting into teaching degrees leads to gains in the labor market, measured 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 demand and supply model of higher education. The model embeds a novel approach to solving discrete-continuous games, in which colleges use their limited computing power in tracking the actions of their closest rivals. The results show that indeed colleges behave in a way that is consistent with bounded rationality, as the model fit decreases when the level of sophistication of colleges increases.

Simulation exercises show that alternative policies achieve a greater 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 degrees produce below-average teachers, even when they attract above-average students. The policy-maker also faces a trade-off between teacher value Added and turnover, since higher value added teachers are also more likely to exit the profession. A wage policy would be orders of magnitude costlier, because of the lack of incentives for colleges to raise admission standards.

While this policy focuses on teachers, the results hold for many professions in which the state is the main employer, such as nurses, judges or social workers. It can also accommodate various constraints faced by the policymaker, such as shortages or a budget-neutral rule. This paper also highlights the fact that, under heterogeneity in training, the higher education stage should be taking into consideration in policy design, as it can lead to a different rule compared to that based on pre-college achievement. Finally, it shows that education policy can be a strong device for recruiting public servants, outperforming more popular policies, such as wage hikes.

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A   Appendix: Additional Figures and Tables

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: This 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.

Table A4: 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 A5: 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 A6: 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 A7: 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 A8: 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 A9: 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 A10: 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 degrees. Bandwith selection is obtained for each characteristic independently. The dummy variable *Santiago* takes value 1 if the individual lives in the capital city. Family income is categorized in 1-10 brackets. 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 A11: 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 A12: RD estimates of retaking College 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 A13: 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 A14: Estimates of enrollment by income at the 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).

Table A15: 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 A1: Robustness checks

(a) Scholarship Takeup

(b) Test Score density
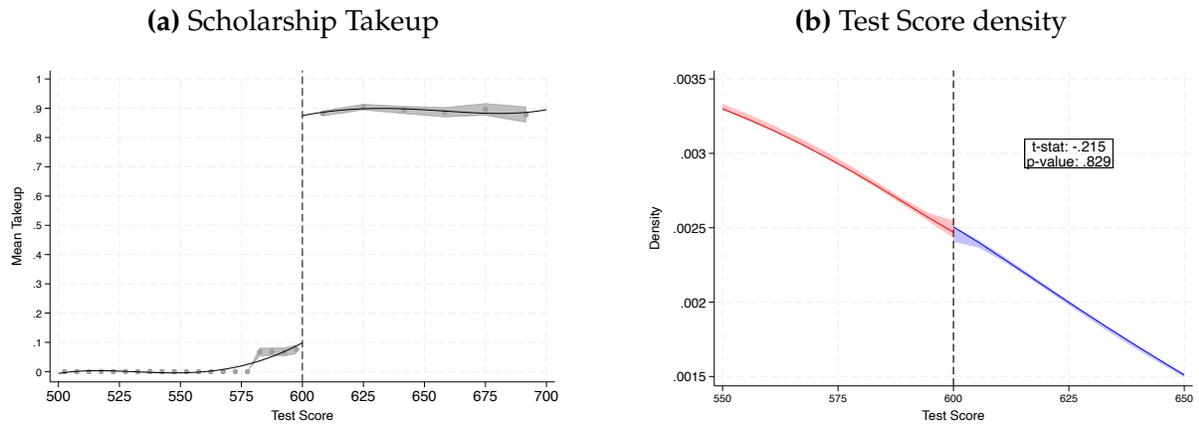
NOTES: Figure A1a plots mean scholarship takeup among all test takers within bins of test scores, with a quadratic fit on each side of the 600 points threshold. Figure A1b shows the kernel density estimation of test scores, and the results from the manipulation test of Cattaneo et al. (2020). Both figures are obtained using the 2011 data.

Figure A2: Dynamic DID estimates of performance
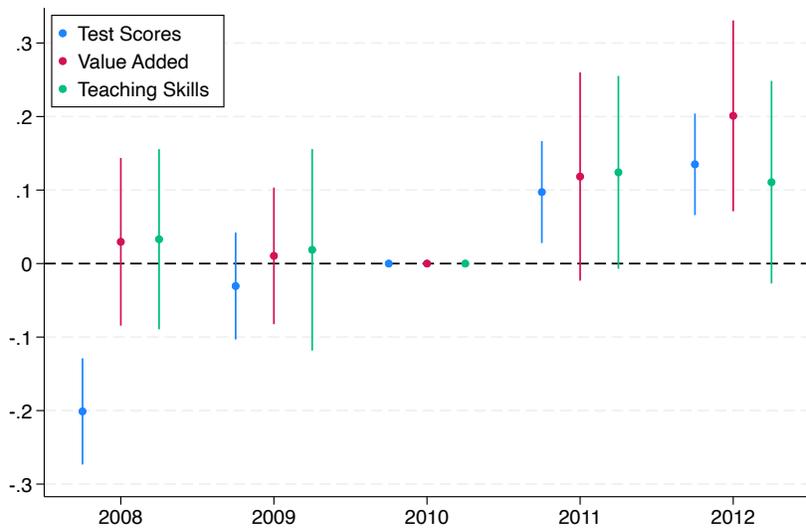
NOTES: This figure shows the result of the event-study design of the difference in performance over time of students enrolling participating and non-participating degrees. The sample is composed of primary school teachers from the 2008-2012 cohorts. For Test Scores, it includes teachers from every grade, 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.

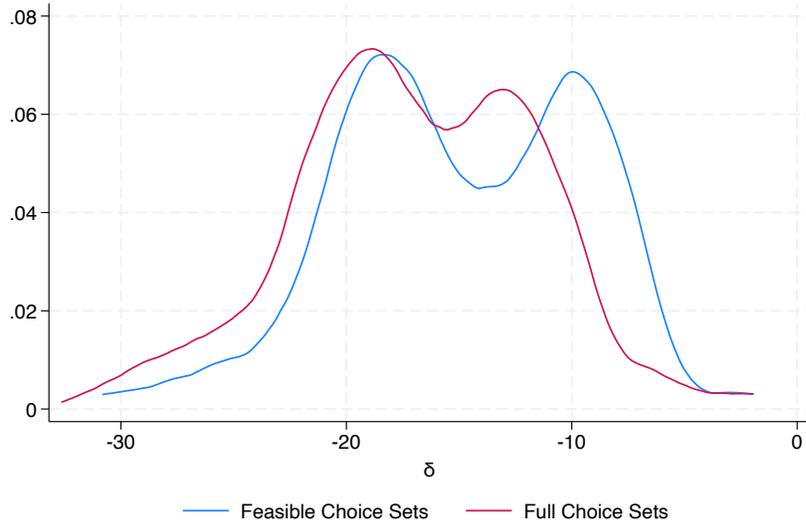**Figure A3:** Supply-side estimation

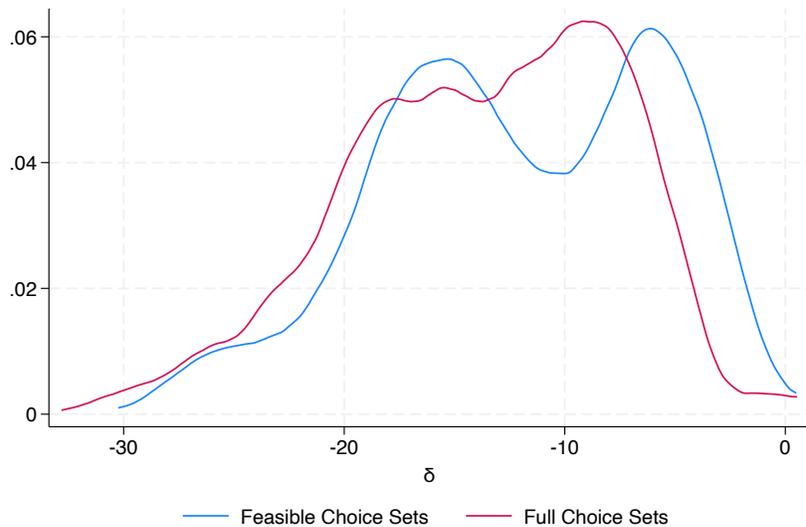**(a)** Costs
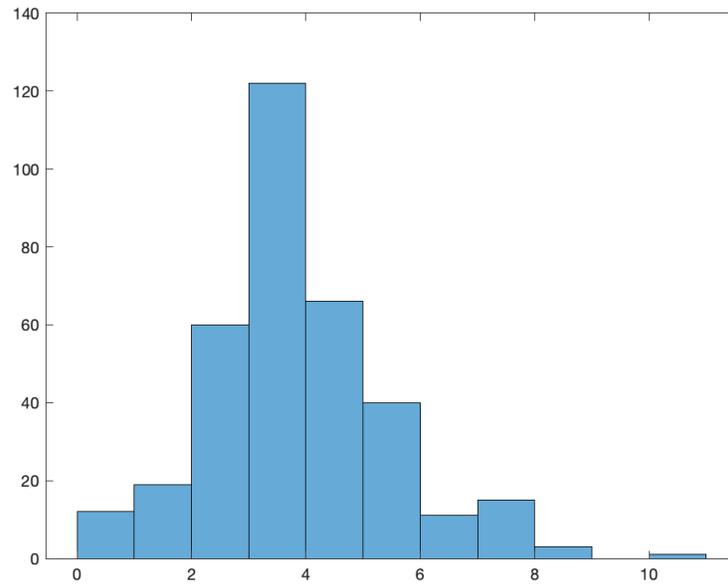
(b) Markups
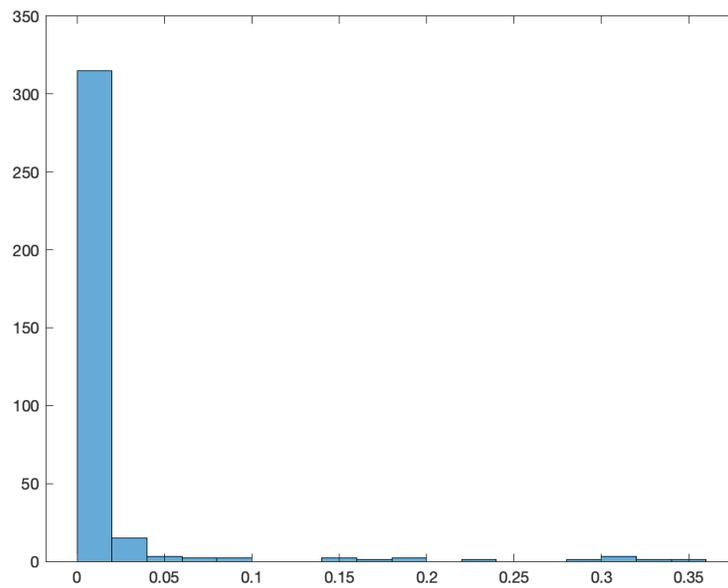
NOTES: This figures show the distribution of marginal costs and markups, as recovered from Equation 17. Marginal costs are expressed in thousands of US dollars.

**Figure A4:** Distribution of Mean Valuation (δ_j)

(a) Low Income

(b) High Income

NOTES: This figures show the distribution of the products' mean valuation (δ_j), for the case in which the market shares are derived from the full choice set of each individual, and the case in which the market shares are derived from the feasible choice set of each individual, depending on his scores at the college entrance exam, and the weights set by colleges on a degree-by-degree basis.

Figure A5: Model Fit of Teacher Value Added, varying number of control function parameters
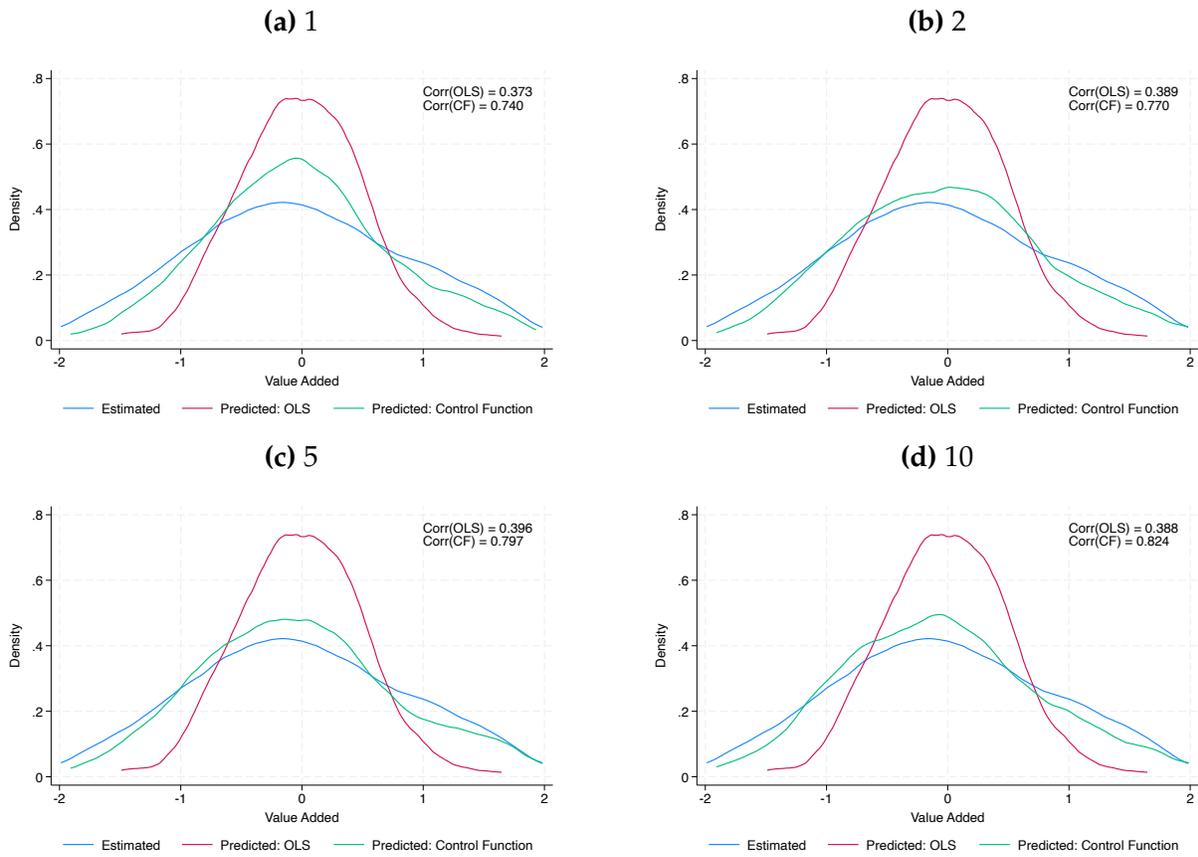
(a) 1

**(b)** 2

(c) 5

(d) 10

NOTES: This figure shows the model fit for estimating Equation 18, as well as an OLS specification that does not control for unobserved heterogeneity. The blue line shows the distribution of the estimated Teacher Value Added for students who enrolled in an Education program and later worked as teachers. The red lins is the OLS prediction based on pre-college observable characteristic. The green line corresponds to the control function approach, where in each case the number of parameters corresponds to the highest utility options within the feasible choice set of each individual.

Figure A6: Model Fit of Teacher Value Added, varying number of control function parameters (continued)
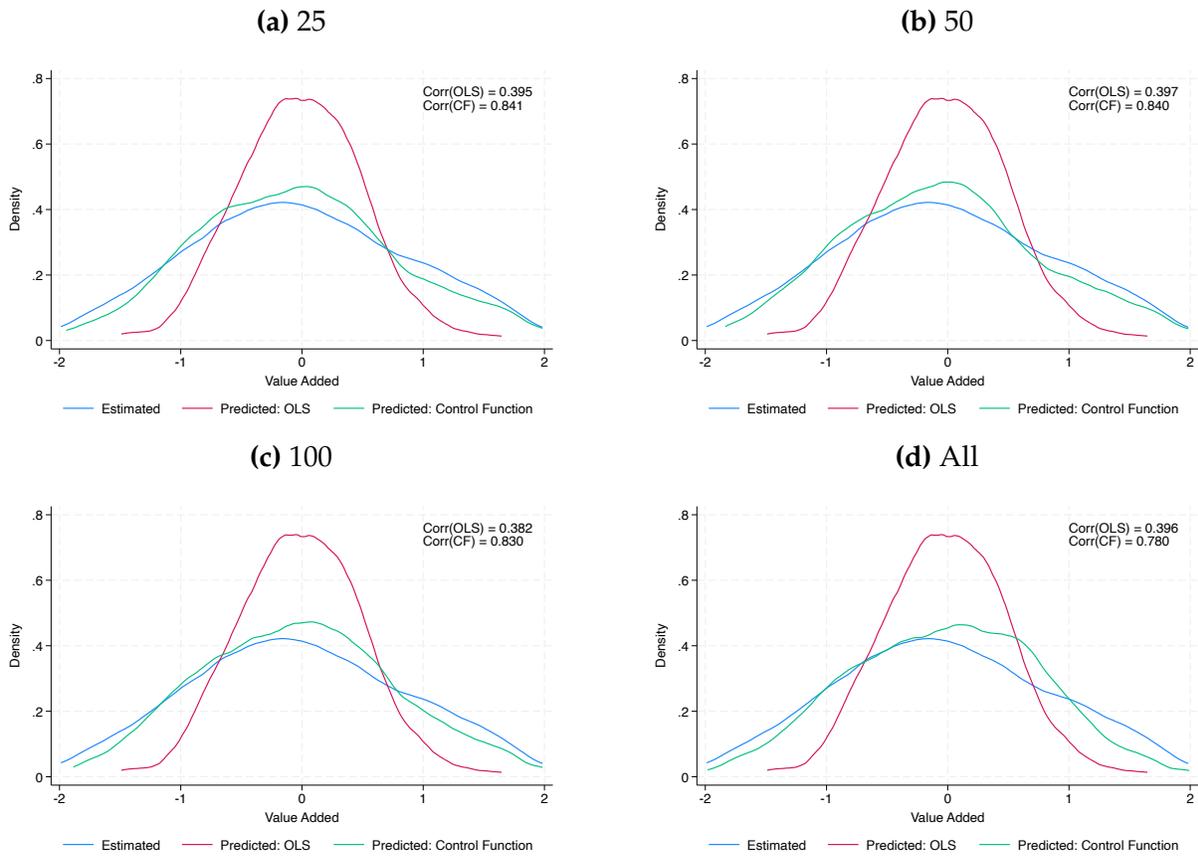
**(a)** 25

(b) 50

(c) 100

(d) All

NOTES: This figure shows the model fit for estimating Equation 18, as well as an OLS specification that does not control for unobserved heterogeneity. The blue line shows the distribution of the estimated Teacher Value Added for students who enrolled in an Education program and later worked as teachers. The red line is the OLS prediction based on pre-college observable characteristic. The green line corresponds to the control function approach, where in each case the number of parameters corresponds to the highest utility options within the feasible choice set of each individual.

Figure A7: Degree Value Added
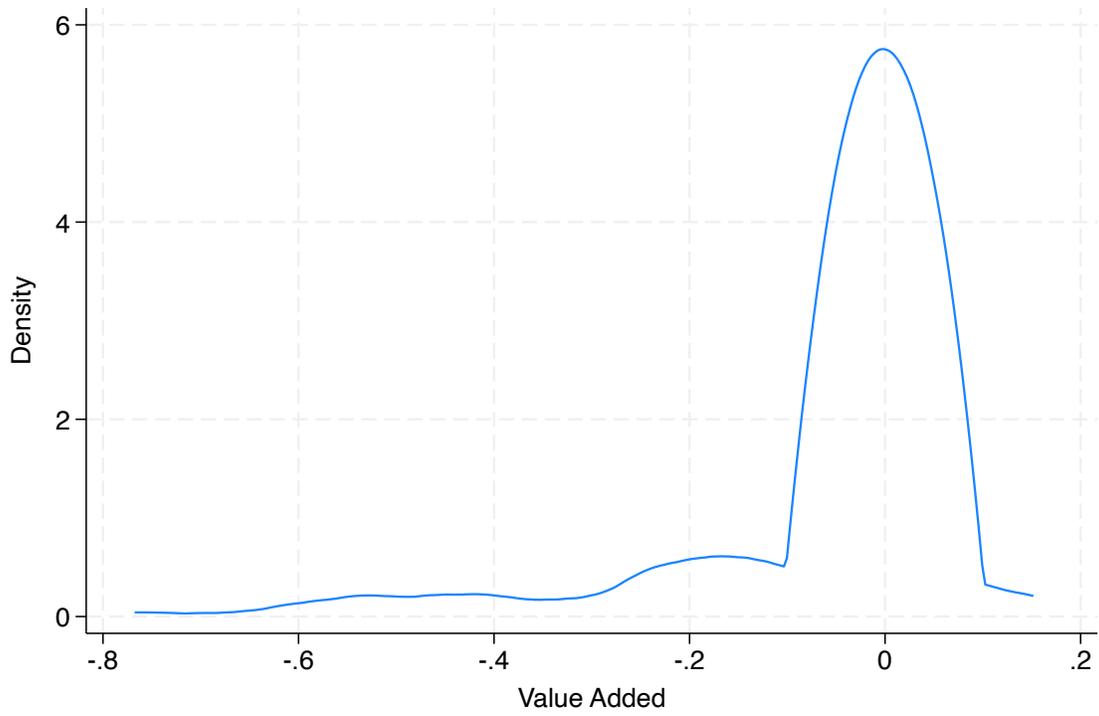
NOTES: These figure plots the distribution of Value Added of Education degrees, resulting from estimation of Equation 18.

Figure A8: Simulated Outcomes (Means-based Policy)
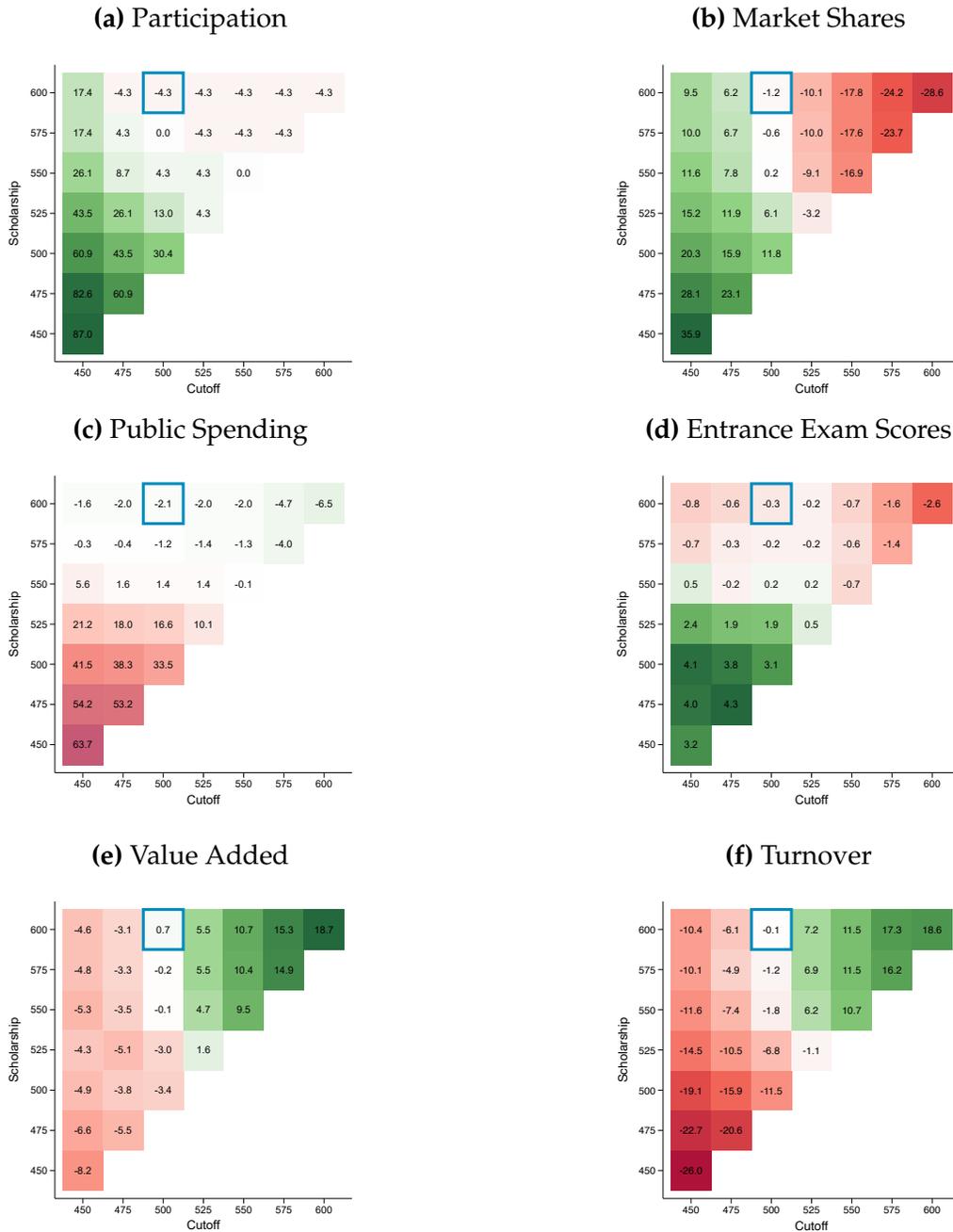
(a) Participation

(b) Market Shares

(c) Public Spending

(d) Entrance Exam Scores

(e) Value Added

(f) Turnover

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. Figure A8a shows the difference in participation rates, Figure A8b shows the difference in market shares for Education degrees, Figure A8c shows the difference in the total amount of public spending, Figure A8d shows the difference in average test scores at Education degrees, Figure A8e shows the difference in teacher value added and Figure A8f the difference in turnover rates.

B Appendix: Additional Empirical Results

B.1 Placement and Turnover Effects

In this section, I estimate if the policy had an effect on teacher turnover. As explained in Section 3.1, 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 B1 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.

Table B1: Estimates of Placement and 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).
*** $p < 0.01$, ** $p < 0.05$, * $p<0.1$

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 B2 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 B2: Estimates of Placement and Turnover (DID)

	(1) Private School	(2) Turnover
ParticipantCollege	0.01***	0.00
	(0.00)	(0.01)
Post=1 × 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C Appendix: Additional Simulations

C.1 Approximating Nash Equilibrium

In this appendix, I present additional simulations to further assess the equilibrium concept developed in Section 5.4. As discussed, the equilibrium model incorporates a bounded rationality approach, where each institution considers the strategic actions of a subset of its closest competitors—its "close rivals"—rather than tracking every player in the market, as in the Nash equilibrium.

To quantify how well limited strategic sophistication (i.e., accounting for only a few close rivals) can approximate full Nash behavior, I conduct the following exercise: For each simulated market size (between 3 and 20 players), I randomly draw a subset of players (private colleges) and solve for both the Nash equilibrium and the sequence of close rivals equilibria, incrementally increasing the number of tracked rivals from 1 upwards. For each draw, I record the minimum number of close rivals required to reach the same outcome as the Nash equilibrium, then average this across 25 simulations.

Table C1 reports the average number of close rivals sufficient to approximate Nash equilibrium behavior as the market size increases. This exercise underscores that, in large settings, Nash equilibrium behavior cannot be captured by monitoring a small number of rivals. Instead, the close rivals equilibrium is only meaningful in environments where bounded rationality is central, and players plausibly neglect the strategic responses of distant competitors.

Table C1: Approximating Nash with Close Rivals

Players	Avg. close rivals
3	1.78
4	2.59
5	3.41
6	4.06
7	4.83
8	5.76
9	6.85
10	8.04
11	8.04
12	8.39
13	9.90
14	11.37
15	11.78
16	12.83
17	13.23
18	14.85
19	16.84
20	17.11

NOTES: Average number of close rivals needed to reach the Nash equilibrium, by number of players.

D   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 case of *Beca Vocación de Profesor*, we have:

$$\lambda_i = \begin{cases} 0 & \text{if } r_i < \bar{r} \\ 1 & \text{if } r_i \geq \bar{r} \end{cases} \tag{22}$$

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:

$$P_{irj} = \frac{e^{U_{irj}}}{\sum_k e^{U_{irk}}} \tag{23}$$

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

$$
\begin{aligned}
s_{rj} &= \sum_{i \in S_r} P_{irj} \\
&= \sum_{i \in S_r} \frac{e^{\alpha_j + \beta(1-\lambda)p_j}}{\sum_k e^{\alpha_k + \beta(1-\lambda_i)p_j}} \\
&= e^{\alpha_j + \beta(1-\lambda)p_j} \sum_{i \in S_r} \frac{1}{\sum_k e^{\alpha_k + \beta(1-\lambda_i)p_j}}
\end{aligned}
\tag{24}
$$

and therefore:

$$\log s_{rj} = \alpha_j + \beta(1-\lambda)p_j + \log \sum_{i \in S_r} \frac{1}{\sum_k e^{\alpha_k + \beta(1-\lambda_i)p_j}} \tag{25}$$

For the outside option, we have

$$\log s_{r0} = \log \sum_{i \in S_r} \frac{1}{\sum_k e^{\alpha_k + \beta(1-\lambda_i)p_j}} \tag{26}$$

Therefore:

$$\log \frac{s_{rj}}{s_{r0}} = \alpha_j + \beta(1 - \lambda)p_j \tag{27}$$

At each side of the threshold, we have

$$\lim_{r \to \bar{r}^-} \log \frac{s_{rj}}{s_{r0}} = \alpha_j + \beta p_j$$
$$\lim_{r \to \bar{r}^+} \log \frac{s_{rj}}{s_{r0}} = \alpha_j \tag{28}$$

which implies

$$\lim_{r \to \bar{r}^+} \log \frac{s_{rj}}{s_{r0}} - \lim_{r \to \bar{r}^-} \log \frac{s_{rj}}{s_{r0}} = -\beta p_j \tag{29}$$

averaging over all degrees, we get

$$-\beta = \frac{1}{J} \sum_{j \in \mathbb{J}} \frac{\lim_{r \to \bar{r}^+} \log \frac{s_{rj}}{s_{r0}} - \lim_{r \to \bar{r}^-} \log \frac{s_{rj}}{s_{r0}}}{p_j} \tag{30}$$

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

$$-\beta = \frac{1}{L} \sum_{l=1}^{L} \left(\pi_l \frac{1}{J} \sum_{j \in \mathbb{J}} \frac{\lim_{r \to \bar{r}^+} \log \frac{s_{rlj}}{s_{rl0}} - \lim_{r \to \bar{r}^-} \log \frac{s_{rlj}}{s_{rl0}}}{p_j} \right) \tag{31}$$

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

$$D_i = \alpha_j + \beta^- \cdot \mathbf{1}\{r_i < \bar{r}\} + \beta^+ \cdot \mathbf{1}\{r_i \geq \bar{r}\}$$
$$+ \sum_{k=1}^{K} \gamma_k^- (r_i - \bar{r})^k \mathbf{1}\{r_i < \bar{r}\} + \sum_{k=1}^{K} \gamma_k^+ (r_i - \bar{r})^k \mathbf{1}\{r_i \geq \bar{r}\} + \varepsilon_i. \tag{32}$$

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

$$\Delta \;=\; \lim_{r \downarrow \bar{r}} \mathbb{E}[D_i \mid r] \;-\; \lim_{r \uparrow \bar{r}} \mathbb{E}[D_i \mid r] \;=\; \beta^+ - \beta^-. \tag{33}$$

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 $\hat{\beta}^+ = \hat{\beta} = \widehat{\Delta}$.

E   Appendix: Simulation of Counterfactuals

This section describes the procedure for simulating the effect of counterfactual policies. The results will depend on L Monte Carlo simulations, and is solved backwards:

1. The platform matches students to degrees.

2. Students anticipate the matching when making their rank-ordered lists.

3. Colleges anticipate the enrollment in each degree when choosing on prices and policy participation.

The education policy is defined by a cutoff threshold $\underline{r}$ and a scholarship threshold $\bar{r}$. Preference parameters (α, δ) and marginal costs c are kept fixed in counterfactuals. Each Monte Carlo simulation $l = (1, ..., L)$ is defined by a random draw of the preference shocks η_{ijl}. I omit the l subscript for ease of exposition.

E.1   Matching

- Given students' preference order $\succ (\eta)$, colleges' index score s and vacancies ν, the mechanism $\phi(\succ (\eta), s, \nu)$ generates the matching μ.

- Given preference shocks η_{ij} and the matching, outcomes Y_{ij} are realized, following Equation 18.

E.2   Demand

Given preference shocks η_{ij}, students compute their utility, as given by Equation 5 and order all programs in a decreasing way, i.e., the preference order $\succ_i (\eta_i)$ is defined.

E.3   Supply

1. For each college, the set of close rivals is defined by the algorithm described in Section 4.5, which depends on demand and supply parameters.

2. The number of close rivals is determined by Equation 21.

3. An equilibrium is searched by an iterative best response algorithm.

4. Colleges form initial beliefs about the (discrete) action of every player (every private college which offers an Education degree).

5. Given beliefs, colleges compute profits for each own action by jointly anticipating:

(a) The price equilibria under the expected action profile (they solve Equation 17).

(b) The matching of the platform under prices and participation decisions.

6. They choose the action that maximizes profits.

7. If each college correctly predict the discrete action of its close rivals, the algorithm stops. If not, players update beliefs of the actions of every player and a new round is initialized.