Should I Stay, or Should I Go? Strategic Responses to Improve College Admission Chances

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I study whether centralized college admission policies that rank students relative to their high school incentivize last-minute school transfers and examine the impact of these actions on long-term outcomes. Exploiting a policy change in Chile and drawing on comprehensive administrative data, I show that students with a high potential increase in their application score are 50 percent more likely to transfer during twelfth grade than students with small potential gains. Heterogeneity analyses indicate that more advantaged public high school students responded strategically to the ranking-based admission policy: after the reform, they were 8 percentage points more likely to take advantage of it than their low-SES peers. Medium-term outcomes suggest that students who gamed the system were more likely to be admitted to and enroll in their first-choice program, although they were not more likely to attend an elite university.

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1. INTRODUCTION

Limited access to college for disadvantaged students has long been a concern among academics and policymakers worldwide. Despite progress, socioeconomic disparities in college attendance persist.[1] In Latin America, for example, only 10% of higher education students in 2018 came from the poorest income quintile—over 50 percentage points lower than the wealthiest quintile (UNESCO, 2020). Increasing opportunities for students from historically disadvantaged populations and communities have been the focus of many different policies.[2] Such policies have been shown to enhance social mobility, equalize opportunity, and redistribute access to higher education without significant efficiency losses or distortions (Bleemer 2021; Chetty et al. 2020; Estevan, Gall, and Morin 2019; Otero, Barahona, and Dobbin 2021; Melo 2024; Black, Denning, and Rothstein 2023; Kapor 2024).

A highly controversial approach to reducing inequality in college access is the special consideration of certain groups in admissions, commonly known as affirmative action (see Arcidiacono, Lovenheim, and Zhu 2015).[3] Although widely used, these policies often generate incentives for students not directly targeted—many of whom perceive themselves as unfairly disadvantaged—which can, in turn, trigger public backlash, legal challenges, and strategic behavior aimed at gaining an advantage within the system.[4] Despite the significance and controversy, relatively little is known about whether affirmative action policies influence students' pre-college strategic behaviors, such as high school choice

[1] Although the global gross enrollment rate in higher education rose from 19% to 38% between 2018 and 2020, enrollment remains concentrated among wealthier social strata (UNESCO).

[2] These include preferential admissions (e.g., quotas or affirmative action) (Otero, Barahona, and Dobbin 2021; Antonovics and Backes 2014; Kapor 2024), financial aid (Solis 2017; Burland et al. 2022), informational interventions (Cox, Kreisman, and Dynarski 2020), and efforts to reduce uncertainty around college returns (Dynarski et al. 2021). See Deming and Dynarski (2010) for a comprehensive review.

[3] Roughly one-quarter of countries worldwide employ some form of affirmative action to increase representation of historically disadvantaged groups in higher education (Jenkins and Moses 2017). Examples include Texas, where the top 10% of students from each high school can attend any public university in the state (Antonovics and Backes 2014; Kapor 2024); Brazil, which implemented federal university quotas (Melo 2024; Mello 2021); and Chile, which adopted a policy comparing students' GPAs to historical trends within their high school (Larroucau, Ríos Uribe, and Mizala Salces 2015; Reyes 2022).

[4] In the U.S., the Supreme Court has upheld the value of diversity in higher education in cases such as Regents of the Univ. of California v. Bakke (1978), Grutter v. Bollinger (2003), and Fisher v. Univ. of Texas (2016). However, in SFFA v. Harvard (2022), plaintiffs argued that race-conscious admissions harmed Asian-American applicants—members of a historically disadvantaged group.

(Cullen, Long, and Reback 2013; Mello 2021; Estevan, Gall, and Morin 2019).

In this paper, I study high school students' tranfer decisions to a change in the college admission system and examine whether these responses undermined the policy's intended goals. I exploit the 2014 public release of information about a new admissions criterion introduced in 2012 as part of Chile's centralized college admission system.[5] Prior to 2012, college application scores were based solely on students' high school GPA and standardized test scores. The reform added a new component—the relative ranking (RR)—which compares a student's GPA to the average GPA of the three preceding cohorts at the same school. However, the formula for calculating RR score was not disclosed until late 2013. Once public, the structure of the new component created incentives for students to transfer from schools chosen for academic or personal reasons to those where they could improve their RR scores during grade 12—and thereby increase their college application scores and *perceived* college admission chances.

Chile offers a compelling setting for this analysis for several reasons. First, a major challenge in studying students' strategic responses to affirmative action (AA) policies is the lack of detailed data linking primary and secondary education, college applications, and pre-college decisions. Chile overcomes this limitation by providing rich student-level administrative data that captures the full educational trajectory and the college application process (Bodoh-Creed and Hickman 2018). Second, Chile's centralized college admission system features transparent and uniform rules, including a clearly defined matching process in which students submit ranked preferences over degree programs.[6] This structure enables researchers to observe system-wide student–major matches and simulate counterfactual scenarios.[7] Finally, the Chilean education system permits students to transfer schools up to two months before the academic year ends, making it easier to engage in strategic behavior in response to changes in the college admission system.[8]

[5]The centralized system includes the country's most selective and competitive universities, both public and private.

[6]Students apply directly to specific degree programs, such as Economics at the University of Chile.

[7]Centralized college admission systems are increasingly common; the number of countries adopting them has more than doubled since the 1990s (Neilson 2019), making the findings of this paper broadly relevant.

[8]Students in Chile can choose among public, voucher, and private schools and are not assigned to a specific institution.

I construct a unique dataset by combining administrative records from the Ministry of Education (MINEDUC), the centralized college admission system (DEMRE), and the Education Quality Agency (Agencia de la Calidad de la Educación), following cohorts of students who graduated from high school between 2010 and 2018. From these sources, I build an indicator for whether a student transfers schools in grade 12 (separating them in beginning of the year and within the year transfers), calculate the ranking score each student would receive if they graduated from any school in their choice set, and construct a measure of socioeconomic status (SES) using information reported in 10th and 12th grade. I use this dataset throughout the analysis to estimate the causal effect of the policy on school transfers during 12th grade and its effects on students' subsequent college admission and enrollment outcomes.

I begin by exploiting the structure of the application score formula and the centralized college–student matching algorithm to study the policy's intended effects. To evaluate its effectiveness, I simulate student allocations to majors under a counterfactual in which no student switches schools in 12th grade and compare these results to the observed matches after some students behave strategically. Focusing on school performance—a dimension policymakers emphasized when introducing the reform—I find that students from low-performing schools are 8 percent more likely to be admitted to selective colleges under the current policy. In the absence of strategic switching, however, this effect would have reached 12 percent, implying a reduction of more than 30 percent in the policy's potential effectiveness. I further show that the gap in acceptance rates by school performance declined in the year of the policy announcement, suggesting that students' relocation decisions increased their likelihood of being accepted into selected universities.

I then develop a simple school choice model in which students decide whether to transfer high schools, taking the selective college admission cutoff as given. This approach helps clarify the link between students' transfer decisions and the policy's effectiveness—an issue that is not immediately obvious, particularly if potential gains in college application scores from switching are evenly distributed across students. The model produces three key insights. First, holding everything else constant, the policy's impact—measure by changes in the composition of the acceptance pool—depends on students' costs of transfering schools: when switching costs are high, the policy is more effective at increasing acceptance rates for students from low-performing schools.[9] Second, the RR formula means that not all students have incentives to switch, even when switching costs are low. Third, students in high-performing schools are most likely to benefit from transferring, as these schools tend to have higher GPA thresholds, making it easier for such students to improve their relative ranking at a lower-performing school.

Finally, to estimate the causal effect of the policy on strategic switching, I calculate each student's application score across their choice set, which allows me to classify students as having high potential gain, small potential gain, or no potential gain from switching schools in 12th grade.[10] Using a difference-in-differences design, I show that in 2014 the probability of transferring schools in 12th grade increased by 0.6 percentage points (50 percent) among students with high potential gain, relative to those with small expected improvements in their application score. Heterogeneity analyses reveal that this effect is entirely driven by students in Santiago, the capital, who attend high-quality public schools, are high-SES, and have parents reporting high educational aspirations for them.[11] These results are consistent with the predictions of my model.

Related literature. This paper relates to several strands of the literature. First, it contributes to the study of the unintended consequences of educational policies, particularly at the pre-college stage of the human capital accumulation process. Previous research has shown that college admission policies affect students' effort (Grau 2018; Bodoh-Creed and Hickman 2018; Tincani et al. 2021; González and Johnson 2018), time spent studying (Caldwell 2010), attendance (Akhtari, Bau, and Laliberté 2024), dropout rates (Cáceres-Delpiano, Giolito, and Castillo 2018), high-stakes exam performance (Antonovics and Backes 2014; Bleemer 2021; Akhtari, Bau, and Laliberté 2024; Laajaj, Moya, and Sánchez 2022), and racial segregation in high schools (Estevan, Gall, and Morin 2019). I contribute

[9] Low-performing schools are defined as those with historically lower average GPAs.
[10] Given the formula, I can calculate potential gains for all cohorts in my sample.
[11] I measure aspirations using parents' responses to the SIMCE questionnaire.

to this literature by showing that a policy rewarding students based on the high school they graduate from can trigger unintended behavioral responses among students who are not the policy's intended beneficiaries.

A closely related body of work examines how AA policies influence school choice (Cullen, Long, and Reback 2013; Mello 2021; Estevan, Gall, and Morin 2019). These studies document student responses to policies that grant direct access to college for students from certain high schools—such as the Texas Top Ten Percent Law (Cullen, Long, and Reback 2013) and Brazil's federal university quotas (Mello 2021). Building on this literature, I show that high-socioeconomic-status (high-SES) students are more likely to respond strategically to the policy. I also quantify how much more effective the policy would have been in the absence of strategic school switching. I am able to make this contribution due to access to detailed student-level data, including application scores and the centralized matching algorithm, as well as school-level identifiers at the start and end of each academic year. This dataset allows me to assess the role of switching in shaping equilibrium student-major assignments—an analysis not possible in prior work such as Cullen, Long, and Reback (2013) and Mello (2021).

Additionally, this paper contributes to the literature evaluating the effects of college admission policies more broadly. This literature has shown that both the context and design of these policies shape outcomes for disadvantaged students (Andrews and Stange 2019; Angrist, Autor, and Pallais 2020; Harris and Mills 2021; Kapor 2024; Long, Saenz, and Tienda 2010), and examined their distributional effects (Otero, Barahona, and Dobbin 2021; Bleemer 2021; Black, Denning, and Rothstein 2023; Melo 2024; Reyes 2022; Bucarey 2017). I contribute by providing evidence that the design of the RR policy—specifically, its dependence on relative performance within high school—induced strategic pre-college responses that reduced its effectiveness. My paper is especially related to Reyes (2022), who studies the same policy's effects on enrollment, graduation, and labor outcomes during a period when the RR formula was not publicly disclosed. I complement that work by focusing on behavioral responses to the policy once the incentives became transparent, and by examining their consequences for college admission rates.

My results also add to the large literature investigating which school characteristics are valued by parents and students, e.g., school quality (Epple, Figlio, and Romano 2004), high-stake exams (Angrist, Pathak, and Walters 2013), peer quality (Abdulkadiroğlu et al. 2020; Abdulkadiroğlu, Agarwal, and Pathak 2017; Haeringer and Klijn 2009; Rothstein 2006; Epple, Figlio, and Romano 2004), college attendance, earnings (Abdulkadiroğlu et al. 2020), and crime (Beuermann et al. 2022). I contribute to this literature by showing that students' original school preferences—based on quality or other factors—can be overturned when the perceived college access benefits of switching are large enough. While it is generally assumed that families avoid lower-performing schools when other characteristics (e.g., distance, cost) are similar, my findings show that this preference can shift when strategic gains are available.

Finally, this paper contributes to research on the effects of relative grading on student outcomes (Calsamiglia and Loviglio 2019; Elsner and Isphording 2017; Diamond and Persson 2016; Rangvid 2015). Consistent with prior findings, I show that students in higher-performing schools may receive lower college application scores due to their lower relative ranking, which incentivizes some to transfer to lower-performing schools to improve their admission prospects.

The rest of the paper is organized as follows. Section 2 describes the institutional setting. Section 3 presents the data. Section 4 examines the effects of the policy by school performance and socioeconomic background. Section 5 introduces a stylized model to understand the incentives for switching schools and their equilibrium effects. Section 6.1 explores how potential application score gains relate to students' characteristics. Section 6.2 outlines the empirical strategy and results for students' switching behavior. Section 6.4 discusses the broader implications of targeting students based on high school attended. Section 7 concludes.

2. INSTITUTIONAL BACKGROUND

Although Chile is a middle-income country with a GDP per capita of approximately USD 14,750 in 2019,[12] income and educational inequality remain high. According to World Bank estimates, Chile's Gini coefficient was 44.4 in 2017—comparable to that of the United States, which stood at 41.4 in 2018. Educational attainment statistics also reveal striking disparities: in 2019, 85.2% of adults aged 25 to 34 had completed at least high school, but only 33.7% had attained a higher education degree. Furthermore, Narayan et al. (2018) ranks Chile among the least socially mobile countries in the world, based on the share of individuals born into the bottom half of the income distribution in the 1980s who reached the top quartile as adults.

2.1. Secondary Education in Chile

The graduation rates in secondary school in Chile are high. In 2019, the dropout rate for grades nine to twelve was less than three percent (Arias Ortiz et al. 2024). However, there are significant differences in the quality of high schools attended by students from different socioeconomic backgrounds. Figure 1 presents the relationship between schools' ranking and the percentage of students receiving free lunch in 2010. The figure shows a strong positive correlation (0.79), indicating that lower-ranked schools—those with weaker academic performance—tend to serve a larger proportion of socioeconomically disadvantaged students.

The link between school quality, students' socioeconomic status, and access to higher education has been a key driver of education policy reforms in Chile. In 2011, the country witnessed one of the longest student-led protests in its history, known as the "Chilean Winter," which called for structural changes to the education system.[13] Advocates for reform argued that students from low-quality schools face significantly lower chances of attending college—regardless of their individual ability or academic performance—due to

[12] Source: World Bank.

[13] The current president of Chile was one of the leaders of this movement. See: `https://www.theguardian.com/world/2021/nov/18/a-fairer-chile-ex-student-leader-bids-to-reshape-country-in-divisive-election`.

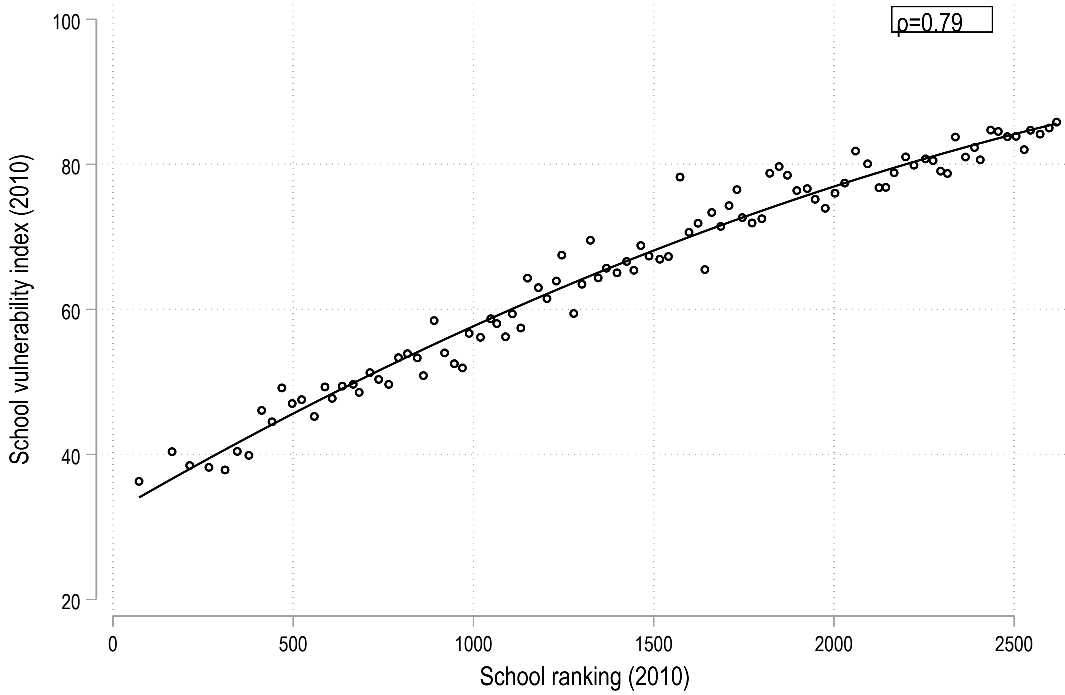


FIGURE 1. School vulnerability index & school ranking

Note: This figure presents the associations between school ranking (x-axis) measured using standardized school tests in grade 10 in 2010 and school vulnerability index (IVM) measured as the percentage of students getting free lunch (y-axis) in 2010.

systemic disadvantages tied to school quality. The Relative Ranking (RR) policy examined in this paper was introduced in response to these concerns. It was designed to expand college access for high-performing students by accounting for the quality of the school they attended (see Section 2.3 for details).

2.2. Tertiary Education in Chile

Most Chilean universities select students through a centralized admissions system, in which applicants are ranked using an application score (AS).[14] Post-secondary institutions in Chile are typically classified as universities (public or private), Centros de Formación

[14]The AS is a weighted sum of three components: the national standardized test (PSU), students' high school GPA, and the relative ranking (RR). The RR component was introduced in 2012 (see Section 2.3 for more details).

Técnica (CFT), or Institutos Profesionales (IP).[15] Of the 144 post-secondary institutions operating in 2014, 25 participated in the centralized system—16 public and 9 private.

Table 1 presents key characteristics of post-secondary institutions in 2014, including average enrollment capacity and tuition, disaggregated by institution type and admission system. Within the centralized system, public universities tend to place greater weight on the RR component and less on the quantitative PSU section compared to private universities. The average enrollment capacity per major is approximately 40 students across institution types, with slightly larger cohorts in private institutions, regardless of the admission system. Average annual tuition (in Chilean pesos) is similar between public and private universities in the centralized system but tends to be higher than at institutions outside the system. Public and private universities also have a comparable distribution of STEM programs and accreditation levels.

Although tuition and other institutional characteristics are similar across types, universities participating in the centralized admission system are generally perceived as higher quality. According to the 2022 Times Higher Education (THE) Latin America ranking,[16] Pontificia Universidad Católica and Universidad de Chile ranked first and seventh, respectively.[17]

From the student's perspective, applying to colleges in the centralized admission system involves three main steps. First, students must complete high school with a GPA of at least 4.0 on a 1–7 scale.[18] Second, they must take the national college entry exam (PSU),[19] which is administered annually in mid-to-late December.[20] Third, students must submit a list of up to ten preferred college-major combinations during the application process. To support families in this process, the organization overseeing centralized admissions

[15] CFTs and IPs are comparable to U.S. community colleges. They primarily offer two-year programs, often with the option to transfer to a private university upon completion.

[16] Source: https://www.timeshighereducation.com/student/best-universities/best-universities-latin-america.

[17] All other Chilean universities in the top 50 also belong to the centralized admission system.

[18] The centralized system standardizes students' high school GPA (NEM) into a score ranging from 200 (for a GPA of 4.0) to 822 (for a GPA of 7.0), based on the average across all four years of high school.

[19] The PSU includes mandatory verbal and quantitative sections, as well as an elective test in either history or science. Each test is normally distributed with a mean of 550 and a standard deviation of 110, with scores truncated at 220 and 850 points.

[20] The academic year in Chile runs from March to December.

TABLE 1. College main characteristics by allocation system and type of institution (2014).

	Centralized Admission		Decentralized Admission		
	Public Univ.	Private U - Crunch	Private U not-Crunch	IP	CFT
	(1)	(2)	(3)	(4)	(5)
Panel 1: *College characteristics*					
Slots	38.00	46.17	43.95	43.95	47.98
Annual tuition (in CLP)	2,198,568.67	2,442,093.45	2,367,721.26	1,238,496.01	1,185,249.22
Ratio stem degree	0.39	0.45	0.33	0.26	0.02
Ratio accredited majors	0.37	0.40	0.32	0.24	0.21
Number of institutions	16	9	34	41	50
Number of programs	853	549	2036	3188	1630
Panel 2: *Enrolled students*					
Total enrollment	39,419.00	29,767.00	76,659.00	126,624.00	65,429.00
Total female enrollment	19,229.00	13,886.00	42,127.00	62,445.00	32,972.00
Panel 3: *Application requirements' weights*					
average weight high school GPA	15.82	17.90	22.75	.	.
average weight relative ranking	26.04	22.60	16.86	.	.
average weight PSU verbal	20.67	18.07	38.08	.	.
average weight PSU quantitative	24.64	28.60	40.93	.	.

Note: This table reports colleges main characteristics by type of institution for students who started college in 2014. Columns (1)-(2) reports average characteristics for universities using the centralized system. Columns (3)-(5) reports average characteristics for universities accepting students via decentralized system.

(DEMRE) maintains an official website with comprehensive information on the process, timelines, and participating institutions.[21]

Students may choose to apply to institutions within either the centralized or non-centralized systems. In 2013, 71% of high school graduates took the PSU, and among them, 45% applied to at least one program in the centralized system.[22]

Applicants to the centralized system are matched to programs using a deferred acceptance (DA) algorithm.[23] A key theoretical property of the DA mechanism is that it is strategy-proof: listing programs truthfully is a dominant strategy, as higher-priority applicants can displace lower-ranked ones in later rounds (Abdulkadiroğlu et al. 2020; Dubins and Freedman 1981; Roth 1982). However, this property assumes students are allowed to rank all programs without restriction (Haeringer and Klijn 2009; Pathak and Sönmez 2013).

Table 3 summarizes students' application behavior and match outcomes. Column 1 shows that more than 90% of applicants rank fewer than ten programs, and about half submit only five preferences—suggesting that the strategy-proof condition holds for the majority of students. Column 2 shows that around 75% of admitted students are matched to one of their top three choices. In the analysis to follow, I interpret students' rank-ordered list as truthful reports of their preferences (Abdulkadiroğlu, Agarwal, and Pathak 2017).

2.3. The Relative Ranking Policy

In June 2012, as a way to support students from low-ranked high schools who had strong GPAs but lower PSU scores, the Consejo de Rectores de Chile (CRUCH) introduced a new component to the existing college admission criteria: the *relative ranking* (RR). This

[21] See https://demre.cl/index for more information.

[22] This paper focuses on students who applied to at least one university through the centralized system for three reasons: (i) the most selective institutions participate in this system; (ii) students have incentives to switch schools only when applying to these universities; and (iii) preferences cannot be recovered for students outside the centralized system. See Barrios-Fernandez (2021) and Larroucau and Rios (2020) for more details.

[23] In each round, students apply to their highest-ranked available program. Programs tentatively accept applicants based on their application score (AS) up to capacity, rejecting lower-ranked students. Rejected students apply to their next choice in subsequent rounds. The process continues until no student can improve their assignment.

TABLE 2. Preferences rankings in the submitted lists (2013).

	Fraction reporting (1)	Fraction admitted (2)
Choice 1	1.000	0.444
Choice 2	0.926	0.194
Choice 3	0.813	0.117
Choice 4	0.592	0.069
Choice 5	0.418	0.050
Choice 6	0.285	0.039
Choice 7	0.197	0.029
Choice 8	0.137	0.021
Choice 9	0.092	0.013
Choice 10	0.064	0.013
Nb. students	119,161	95,568

Note:: This table reports the average characteristics of Chilean applicants to college at the end of 2013 by student preference rank. Column 1 displays fractions of students' applications listing each choice. Column 2 reports the fraction of students accepted in each choice.

criterion compares a student's GPA to the average GPA of the three previous graduating cohorts from the same high school. Importantly, because students are evaluated relative to earlier cohorts at their own school, they do not compete with peers from their same graduating class for a higher RR score.

The standardized relative ranking (RR) score is calculated using a nonlinear transformation of the student's high school GPA. If a student's GPA is below the average of the three previous cohorts at their graduating high school, their RR score is equal to their standardized GPA score (SGPA). If the GPA is above that average but below the highest GPA among those prior cohorts, the student receives a bonus to their score. Finally, if the student's GPA exceeds that of the highest-performing student from the previous three cohorts, they receive the maximum RR score of 850 points. Figure 2 graphically illustrates how the relative ranking is computed. The blue line represents the function mapping a student's four-year high school GPA to their SGPA score, while the red line shows the nonlinear relationship between GPA and the standardized RR score. In the figure, $\underline{r}_S$

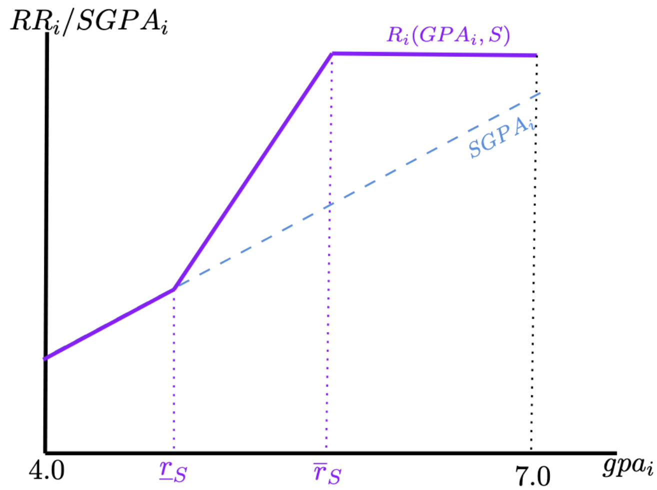


FIGURE 2. Relative ranking component visualization

Note: This graph depicts the formula used in Chile to create the relative ranking (RR). The blue dashed line shows the formula for student's standardized GPA (SGPA) as a function of student's GPA. The purple solid line represents the non-linear formula to calculate the RR as a function of the GPA. $\underline{r}_S$ represents the mean of the three previous cohort who graduated in school S. $\overline{r}_S$ represents the maximum threshold, which is equal to the best student from the three previous cohorts' GPA.

denotes the average GPA across the three previous cohorts, and $\overline{r}_S$ indicates the maximum GPA within those cohorts.

For students to know that they could have some gains if transfer schools in 12th grade, the policy must be salient. I review all the documents available in the college application system's official website and news papers to better understand when the information was made public. Although the policy was implemented in 2012,[24] students were not informed about how the relative ranking (RR) was computed until November 2013. This disclosure clarified that between 2012 and 2014, the RR score was calculated based solely on the student's GPA relative to previous cohorts at the school they graduated from—not all the schools the student may have attended during high school.

[24] Referring to the application processes for admission in the 2013 academic year.

3. DATA

3.1. Data sources

This paper combines multiple administrative data sources from the Chilean educational system, covering students enrolled in 12th grade nationwide between 2010 and 2018. I merge publicly available records from the Ministry of Education (MINEDUC), the centralized college admission system (DEMRE), and the Education Quality Agency (Agencia de la Calidad de la Educación). MINEDUC data provide student-level information such as gender, school enrollment history, and high school GPA, as well as school-level characteristics including geolocation, school type (public, voucher, or private), number of teachers, and other institutional attributes. I also incorporate additional MINEDUC records containing college–major information, including the weights assigned to each application score component, the number of available seats, and program-level details. DEMRE data include national test scores by subject, students' ranked lists of up to ten college–major preferences, and household characteristics at the student–preference level. Finally, from the Education Quality Agency, I obtain students' scores on the 10th-grade standardized test (SIMCE), self-reported socioeconomic status (SES), and parental aspirations for their children.

3.2. Data limitations

Although Chilean administrative data offer rich student-level information, the dataset used in this paper has three main limitations. First, I do not directly observe students' socioeconomic status (SES), as the available data include only self-reported income in brackets—information used to determine financial aid eligibility and thus likely to be underreported. To address this, I use maternal education as a proxy, which offers two advantages: it is not tied to financial aid decisions and is available from both a 12th-grade student survey and a 10th-grade parent questionnaire. While I cannot directly validate its correlation with SES at the individual level, Figure A2 shows a strong school-level association. The correlation between the share of students whose mothers did not complete high school and the school's vulnerability index is 0.7946.

Second, I do not have access to students' home addresses, which limits my ability to precisely define each student's local schooling market. To approximate students' residential locations, I use the geolocation of their primary school as a proxy. Based on this proxy, I construct buffers with radii of 2, 4, 6, and 8 kilometers to define each student's relevant choice set.[25] Figure A3 shows the actual distance between students' primary and high school locations in 2014. More than 70% of 12th-grade students attend a high school located within 5 kilometers of their primary school, supporting the validity of this proxy.

Finally, I do not observe the exact algorithm used by the centralized system to assign students to their chosen majors. To simulate this process, I implement the Deferred Acceptance Algorithm (DAA) developed by Sergey Lychagin.[26] I validate the algorithm using the actual 2014 applicant pool and their recorded application scores. My simulation exactly replicates the real student–major allocations for that year, recovering 100% of the observed matches.

4. EFFECT OF THE POLICY IN COLLEGES ACCEPTANCE RATE

In this section, I look at the effect of the policy on students applying to college in 2014. Recall the policy aims to increase the representation in college of students from lower-ranked schools and students from lower socio-economic status. Overall, I find that when considering school performance, the policy had a smaller effect than it could have if students did not switch schools, reducing the effect to 2/3 of the expected results.

4.1. Descriptive statistics

Table 3 presents the main characteristics of cohorts graduating between the years 2009 and 2013. The first column shows the mean and standard deviation of several students' and their high schools' characteristics. Overall, almost 75% of the students have mothers

[25] This approach is motivated by findings in the school choice literature, which documents a strong relationship between distance and school choice in the context of primary education (Neilson 2013; Allende 2019).

[26] See `https://github.com/lychagins/gale-shapley-matlab`.

with at least a high school diploma, and 30% of students live in the metropolitan area of Santiago.[27] Most of the students in the country attend public (33%) or voucher schools (53%). When considering school quality, measured using tenth-grade standardized test scores taken in 2010, 50% of the students applying to college are in high-quality schools.[28]

Each of the rows in columns (2) to (4) reports the OLS coefficient and standard errors, in parentheses, of a regression of students' characteristics on a dummy variable equal to 1 if the student was accepted in college (column 2), accepted into one of the two most selective colleges (column 3) or accepted into the other 8 more selective Chilean universities (column 4), clustering standard errors at the municipality level.[29] In general, students considered high achievers with mothers who have at least a high school diploma are more likely to get accepted in college, with more pronounced differences in the rate of acceptance for the top two colleges in the country. Interestingly, although students in metropolitan region are not more likely to get accepted in any college, they are 35% more likely to be accepted in the top colleges. Students from public and charter schools are less likely to get acceptance in top colleges, and students from high quality schools are more likely to get any acceptance. These statistics are consistent with the government's priors to the RR policy, and the main reason why they incorporated it; students from less privilege backgrounds are less likely to get accepted in college.

Table 4 present descriptive statistics for students in twelfth grade between 2010 and 2013 (baseline). On average, 42% of students are in public high schools and 49% percent in voucher schools. In this period, on average 3.5% of students switch schools, this mean is slightly higher (lower) for students from high (lower) SES. When considering different characteristics of students and school, we observe that high achievers are less likely to switch schools, while students in voucher schools are about half of a percentage point more likely to switch schools. Finally, students in high quality schools are less likely to

[27] In Chile, the main region is the metropolitan region (RM), where Santiago, the capital of Chile, is located. RM represents, in 2014, the 38% of all the students in Chile. The second most important region is Valparaiso representing 10% (~10.40%) of all students (twelfth grade).

[28] I create 4 categories of school using their pre-policy ranking: high-quality schools (highest quartile), middle-high quality (third quartile), middle-low quality (second quartile), and low quality (first quartile).

[29] Students are observed only once in this sample. Municipalities are the smallest geographical area I observe for each student.

TABLE 3. Descriptive Statistics. Universities' acceptance rate (2009-2013).

	Mean & Standard deviation	Accepted	Tier 1	Tier 2
	(1)	(2)	(3)	(4)
Panel A: *Outcome variables*				
Unconditional mean		0.76	0.15	0.36
		(0.43)	(0.36)	(0.48)
Mean for mothers'education < *HS*		0.69	0.06	0.35
		(0.46)	(0.24)	(0.48)
Mean for mothers'education = *HS*		0.75	0.12	0.37
		(0.43)	(0.32)	(0.48)
Mean for mothers'education > *HS*		0.82	0.27	0.36
		(0.38)	(0.44)	(0.48)
Panel B: *Students'characteristics*				
High achiever	0.47	0.22***	0.18***	0.05***
	(0.50)	(0.01)	(0.02)	(0.02)
Female	0.51	-0.07***	0.01***	-0.08***
	(0.51)	(0.00)	(0.00)	(0.01)
Mothers'education < *HS*	0.24	-0.09***	-0.11***	-0.01
	(0.24)	(0.00)	(0.02)	(0.01)
Mothers'education = *HS*	0.50	-0.01**	-0.05***	0.01**
	(0.50)	(0.00)	(0.01)	0.01)
Mothers'education > *HS*	0.26	0.09***	0.17***	-0.00
	(0.26)	(0.00)	(0.03)	(0.01)
In metropolitan region	0.30	-0.01	0.35***	-0.05
	(0.46)	(0.01)	(0.04)	(0.04)
Panel C: *High schools'characteristics*				
Public schools	0.33	-0.05***	-0.09***	-0.05
	(0.47)	(0.01)	(0.02)	(0.01)
Charter schools	0.53	-0.01	-0.11***	0.02
	(0.50)	(0.01)	(0.03)	(0.02)
Private schools	0.14	0.12***	0.38***	-0.04
	(0.35)	(0.01)	(0.06)	(0.04)
School's quality 1st quartile	0.07	-0.16***	-0.06***	-0.06***
	(0.25)	(0.01)	(0.01)	(0.01)
School's quality 2nd quartile	0.15	-0.09***	-0.04***	-0.03***
	(0.36)	(0.01)	(0.01)	(0.01)
School's quality 3rd quartile	0.27	-0.02***	-0.04***	0.00
	(0.45)	(0.00)	(0.01)	(0.01)
School's quality 4th quartile	0.50	0.10***	0.06***	0.03***
	(0.50)	(0.00)	(0.01)	(0.01)
Observations		432,512	432,512	432,512

Note:: * $p < .10,^{**} < .05,^{***}$ $p < 0.01$. Column 1 presents sample means and standard deviations, in brackets, of cohort applying to college at the end of the 2009 and 2010 years. Column (2)-(4) are calculated with OLS and clustering standard errors (in parenthesis) at the municipality level. Column (2) reports the OLS coefficient of a regression of the student's characteristics on a dummy variable equal to one if student was accepted in *any* university through the centralized application system. Column (3) reports an OLS coefficient of a regression of the student's characteristics on a dummy variable equal to one if the student was accepted in the two *most selective* universities. Column (4) reports an OLS coefficient of a regression of the student's characteristics on a dummy variable equal to one if the student was accepted in one of the universities ranked between second and tenth in the system.

move on average.

4.2. Policy effects by school's quality

I compute the effect of the policy in the pool of accepted students in college using simulations over the same pool of applicants. I use this methodology for two reasons. First, the policy timeline makes harder to use any type of difference-in-difference design controlling for trends (see Figure A4). Second, I am interested in the total distributional effects of the policy, so any design, such regression discontinuity will only capture the effect on the marginal student.

To calculate the allocation of students into college without the policy, I leverage the formula used to calculate students' application score in 2011 and compute, for students applying to college in 2014, what would be their score with this old formula. I also calculate students application score with and without relocation. I do this for the real score (the one students have after the switching school decisions) to reduce concerns about measurement error. Similarly, I use majors' available slots in 2014, to eliminate allocation changes due to increases/reductions in the slots available between different years, Figure A6 in appendix C presents the average number of slots in the system between years 2010 to 2014.

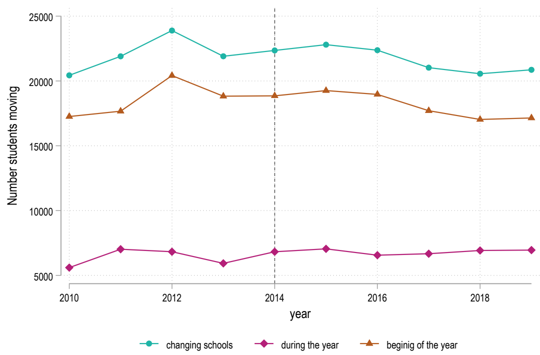
For the first assumption, there are two facts that reduce the concern. First, I focus on students who switch in graded twelfth, while the SGPA and PSU considers grades and knowledge, respectively, obtain during all high school (grades 9 to 12). Further, Figure 3 presents the number of student switching schools in twelfth grade from 2011 to 2015, depending on when they switch,[30] for all students (panel a) and for students in a top schools in the country (panel c). The trend suggests students spend less than a year in the new school, since the increase is mostly derive by movers during the year, reducing the concern of potential changes in PSU score and NEM after switching schools. For the second assumption I leverage the college admission system allocation mechanism, since it creates incentives for students to truly reveal preferences (see Subsection 2.2).

[30] I consider a student switches at the beginning of the year if they appear in the school at the end of eleventh grade, but they appear in a different school at the beginning of twelfth grade.

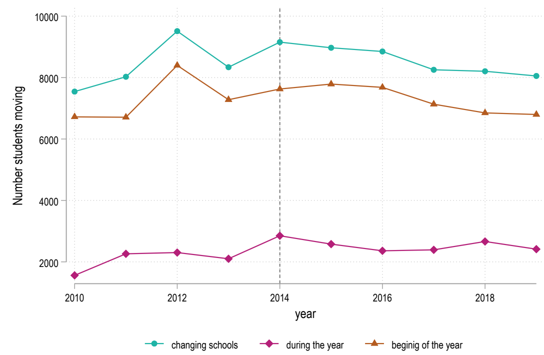
TABLE 4. Descriptive Statistics. Students' characteristics in switching decision (2010-2013)

	Mean & Standard deviation	Swiching schools
	(1)	(2)
Panel A: *Outcome variables*		
Unconditional mean		0.035
		(0.184)
Mean for low SES		0.028
		(0.164)
Mean for medium SES		0.034
		(0.181)
Mean for high SES		0.036
		(0.186)
Panel B: *Students'characteristics*		
High achiever	0.489	-0.012***
	(0.500)	(0.001)
Female	0.517	-0.007***
	(0.517)	(0.001)
Low SES	0.376	-0.007***
	(0.376)	(0.001)
Medium SES	0.429	0.003***
	(0.429)	(0.001)
High SES	0.196	0.005***
	(0.196)	(0.002)
In metropolitan region	0.386	0.001
	(0.487)	(0.002)
Panel C: *High schools'characteristics*		
Public schools	0.424	-0.003**
	(0.494)	(0.001)
Vouher schools	0.485	0.005***
	(0.500)	(0.001)
Private schools	0.091	-0.006**
	(0.287)	(0.002)
School's quality 1st quartile	0.164	0.014***
	(0.371)	(0.002)
School's quality 2nd quartile	0.236	0.002*
	(0.425)	(0.001)
School's quality 3rd quartile	0.279	-0.006***
	(0.449)	(0.001)
School's quality 4th quartile	0.320	-0.005***
	(0.467)	(0.001)
Observations		806,120

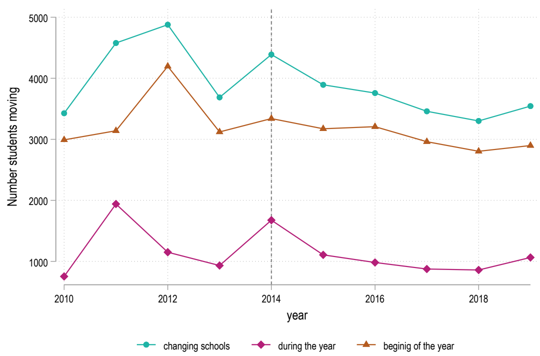
Note: $^{*}\ p < .10,^{**} < .05,^{***}\ p < 0.01$. Column 1 presents sample means and standard deviations, in brackets, of cohorts applying to college at the end of 2014. Column (2) is calculated with OLS and clustering standard errors (in parenthesis) at the municipality level. Column (2) reports the OLS coefficient of a regression of the student's characteristics on student potential gain.



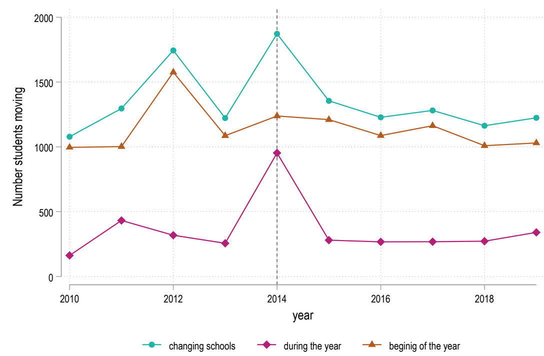
A. *All* students



B. Students in Santiago



C. Students in *high-performing* schools



D. Students in *high-performing* schools in Santiago

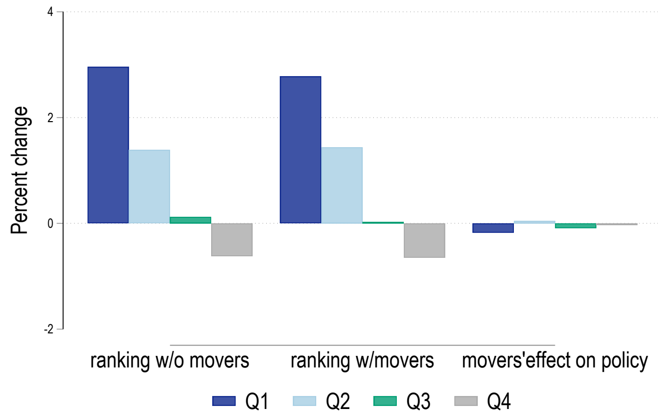
FIGURE 3. Number of students switching schools in twelfth grade (2010-2019)

Note: This figure reports the total number of students switching schools in 12th grade by year. In each panel, circles indicate the total number of students switching schools in that year, triangles represent switches occurring at the beginning of 12th grade, and diamonds represent switches taking place during 12th grade (April to October).

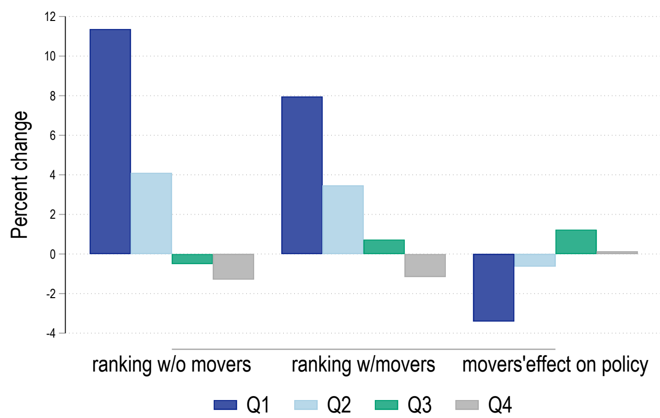
I present results for students by school in Figures 4 and A5 considering overall rate of acceptance and acceptance rate in tier 1 colleges. Figure 4A presents the results by initial school quality. In the first exercises (four first columns), I calculate the effect of the policy if students graduated from the school they started the year (*benchmark effect*). In this case, I find that the policy would increase the number of accepted students from low quality schools, in the centralized system, by 3 percents. I find a similar results when student switches schools (*real effect*), showed in the next four columns. I argue this is expected since the rate of acceptance conditional on applying to *any* college is about 80% in 2014 (see Figure A6).

Results are different when analyzing acceptance rate in most selective universities (see Figure 4B). In this case, the policy effectiveness is reduced by 1/3 of the results it would have had if students did not switch schools. Here the effect of the movers decrease the effect of the policy in more than 3 percentage points (last four columns). These results are consistent with the drop in the acceptance rates of Tier 1 and 2 universities observed in 2014 (see figure 5).

In summary, I find that the RR policy increase the number of students accepted in *any* college, but could be more effective if students did not switch schools strategically. The policy is more effective when considering the school's quality where students started the last academic year of high school than considering student's SES. The results are in line with Larroucau, Ríos Uribe, and Mizala Salces (2015) which finds modest effect of the policy using cohorts applying to college in 2012 and 2013. This results could come from different channels. Due to the implementation used in this AA policy we might expect that students' effort and switching decision would change with the policy, which could affect the policy goal in unintended ways. González and Johnson (2018) analyzes the effect of the policy for cohorts applying to college in 2012 and 2013 and find that effort did not change. I focus on the effect of switching schools in grade twelfth.



A. Acceptance rate in *any* university



B. Acceptance rate in *tier 1* universities

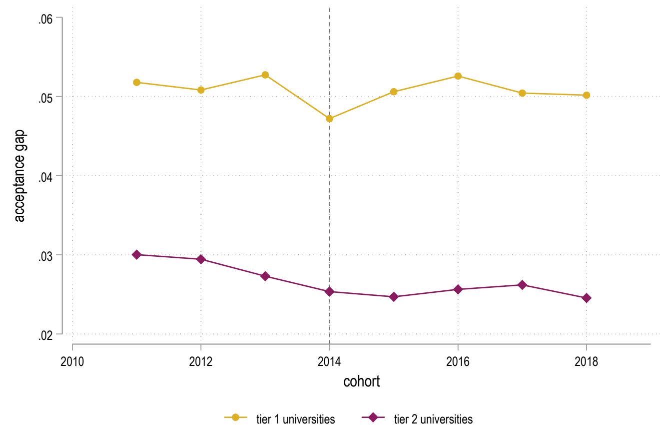
FIGURE 4. Policy effects in cohort applying to college in 2014 by schools' quality.

Note: This figure depicts the percentage change in the number of students accepted in college by school's quality. Denominator in the percentage is the number of students accepted into each category without the policy. Figure (a) presents the changes in rate of acceptance in any university. Figure (b) presents the policy effect for tier 1 colleges (top-2 universities).

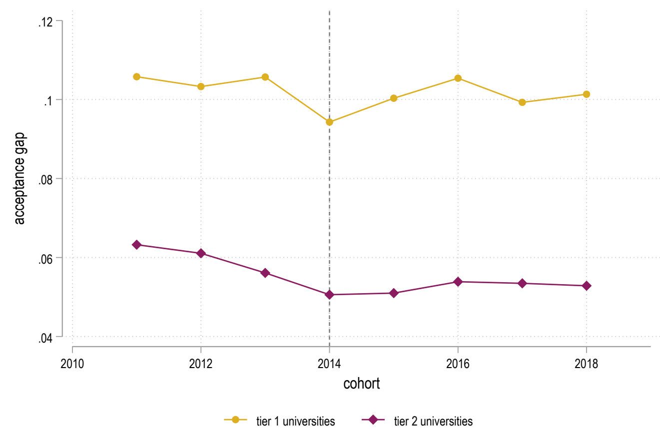
5. CONCEPTUAL FRAMEWORK

I build a theoretical model to understand who has incentives to game the policy by switching schools. Since the policy compared students within the school they graduated from, students have no reason to move early, therefore, I focus on twelfth graders' switching decision.

In the first part of this section, I build theoretically students' potential gain due to



A. Acceptance rate gap in tier 1 universities



B. Acceptance rate in *tier 2* universities

FIGURE 5. Acceptance gap at selective universities.

Note: This figure depicts the change in the acceptance rate gap between high-quality and low-quality high schools in selective universities (tier 1 and 2). Figure (a) presents the changes in the gap for the country. Figure (b) presents the change in the gap for Santiago. Here students are considered only in the school they graduated from.

the policy. Next, I present a model for switching decisions that incorporates the cost of switching. I end this section by analyzing how the application cutoff and college body composition change in different scenarios.

5.1. Potential gain in students' application scores

I assume that there are two high schools L, and H, one college, C, and a continuum of students of mass 1 applying to college from both schools. A fraction μ_H of those students is in school H and $1-\mu_H$ in school L. Each high school is characterized by two predetermined variables: the mean threshold, $\underline{r}$, and the maximum threshold, $\overline{r}$, both computed from the **three previous** cohorts graduating from the high school. All thresholds are known when students make their relocation decision in twelfth grade.

I consider a setup where students have already been assigned to one high school, and their only decision is whether or not to switch to a new high school. Although the earlier school choice decision is important, and has been analyzed extensively before (Alves et al. 2015; Pop-Eleches and Urquiola 2013; Hastings, Neilson, and Zimmerman 2012; Neilson 2013; Allende 2019), I consider the school where they start as given and focus on the switching decision only. College C is characterized by its capacity constraint K and its preferences over students application scores. For the purpose of the model, I assume here students score depends only in the relative ranking.[31,32] Students are characterized by their GPA: $gpa_i \in (\underline{g}, \overline{g})$, and their started high school, $s \in \{L, H\}$.

Before the policy, student *i*'s application score (AS_i) is a function of their GPA only:[33,34]

$$AS(gpa_i) = gpa_i + \theta, \tag{1}$$

After the policy, the mapping from student i's GPA to applications scores is determined by a non-linear function of their GPA relative to the school where they graduated from -school *e*-:

$$AS_e(gpa_i) = \begin{cases} gpa_i + \theta & \text{if } \underline{g} \le gpa_i < \underline{r}_e \\ (1+\alpha_e)\cdot gpa_i + \theta_e & \text{if } \underline{r}_e \le gpa_i < \overline{r}_e \\ \overline{AS} & \text{if } \overline{r}_e \le gpa_i \le \overline{g}. \end{cases} \tag{2}$$

This non-linear function implies: (i) student gets the same AS than before the policy

[31] Although in Chile the application scores are determined using weights to each requirement (PSU, high school GPA and ranking).
[32] This assumption is possible if average GPA at high school and PSU scores do not change with the switching decision.
[33] This formula comes from the system. See MINEDUC.
[34] Notice the AS is the same no matter the school student i's graduated from.

if they are not above graduation school's mean threshold, (ii) student obtains a school-specific bonus if they are above the mean threshold but below the maximum threshold in the school, and (iii) student obtains the maximum points possible whenever they have a GPA higher than the best student in the three previous cohort -maximum threshold-.

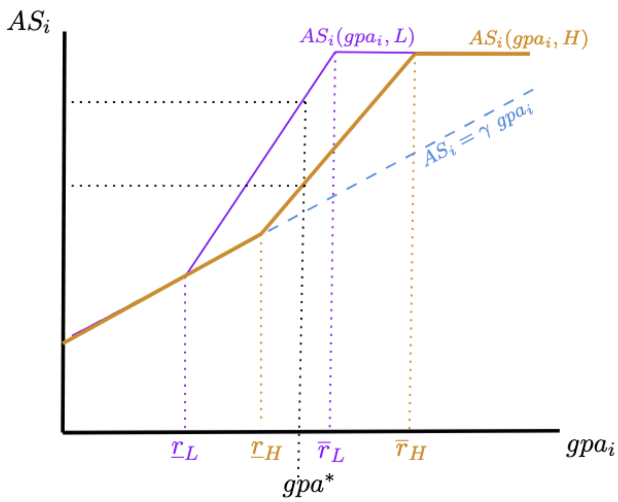


FIGURE 6. Same thresholds' order

Note: This graph depicts the formula used in Chile to create the relative ranking (RR) considering two schools with different thresholds. The orange line shows the formula for students graduating from school H as a function of students' GPA. The purple line represents the RR formula for students graduating from school L. $\underline{r}_L$ and $\underline{r}_H$ represent the mean of the three previous cohort who graduated in school L and H respectively. $\overline{r}_L$ and $\overline{r}_H$ represent the maximum threshold, which is equal to the best student from the three previous cohorts' GPA.

Figures 6 and 7 graphically present the cases for all the possible combinations of threshold between two schools. I assume a student starting twelfth grade in school s has a potential gain in the application score by switching to school e if:

$$AS_e(gpa_i) \geq AS_s(gpa_i),$$

for $s, e \in \{H, L\}$, and $s \neq e$.

In Figure 6 students from school, s have a potential score gain by switching to school e, but no one from school e is better off, in AS sense, switching to school s, I call this case *downward switching*. On the other hand, we can see in Figure 7 that whenever the dispersion within school e's thresholds is lower than in school s, some students in both

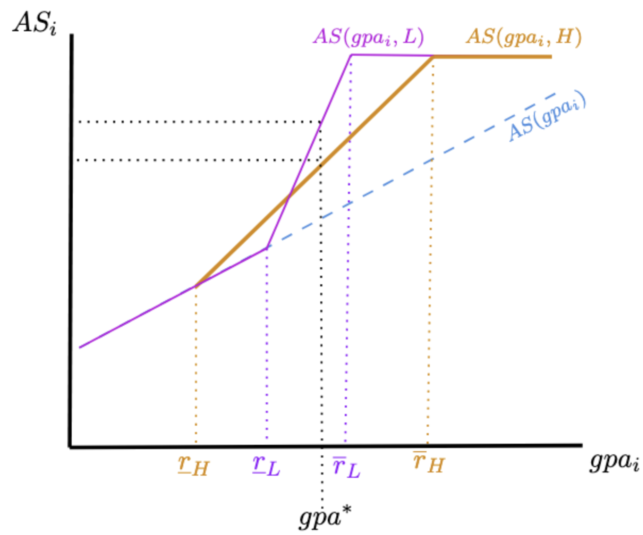


FIGURE 7. Different thresholds' dispersion

Note: .

schools could benefit from switching schools.

5.2. A simple model of switching schools

The model developed in this section builds on Cullen, Long, and Reback (2013) and Estevan, Gall, and Morin (2019) theoretical models. Assume all students are applying to college[35], and derive a utility U_{iC} if they are accepted into it. If they are not accepted, their utility is 0.

All the students are ranked depending of their application score when applying to college. The college allocation mechanisms is such that students with an applications score higher than the cutoff are accepted into college,[36] where the cutoff is an equilibrium outcome.[37]

I assume students pay a cost, $c_{ise} > 0$ of switching from school s to school e for all

[35]Although this is a strong assumption, due to the fact that the policy changes the application scores that might create incentives for some students to switch schools, it is reasonable to only analyze the pool of students interested in the application process.
[36]If K<1 only fraction of the total population, normalized to one, is accepted into college.
[37]Note that other students' decision only affect student i through changes in the equilibrium cutoff to get accepted.

$e \in \{H, L\} - \{s\}$. Additionally, students value each school differently, with $b_{is} > b_{ie}$.[38]

Thus, student's conditional utility from staying in school s is

$$V_{is} = \begin{cases} b_{is} + U_{iC} & \text{if } AS_s(gpa_i) \geq AS^* \\ b_{is} & \text{otherwise,} \end{cases}$$

while their conditional utility if they switch to school e is

$$V_{ie} = \begin{cases} b_{ie} - c_{ise} + U_{iC} & \text{if } AS_e(gpa_i) \geq AS^* \\ b_{ie} - c_{ise} & \text{otherwise,} \end{cases}$$

Next, let $\Delta V_{i(s \to e)}$ be the change in the indirect utility due to switch from school s to school e. Then we can define the change in utility of switching to any school e in the choice set as:

$$\Delta V_{i(s \to w)} = \begin{cases} b_{ie} - b_{is} - c_{ise} < 0 & \text{if } AS_e(gpa_i), AS_s(gpa_i) \geq AS^* \\ b_{ie} - b_{is} - c_{ise} < 0 & \text{if } AS_e(gpa_i), AS_s(gpa_i) < AS^* \\ b_{ie} - b_{is} - c_{ies} - U_{iC} < 0 & \text{if } AS_s(gpa_i) \geq AS^* > AS_e(gpa_i) \\ b_{ie} - b_{is} - c_{ies} + U_{iC} \gtreqless 0 & \text{if } AS_e(gpa_i) \geq AS^* > AS_s(gpa_i). \end{cases} \tag{3}$$

As we can see from equation (3), the only case in which a student has a positive gain in utility is if the student was not above the equilibrium cutoff when graduating from school s, but they would be when graduating from school e, and

$$U_{iC} \geq b_{is} - b_{ie} + c_{ise} = \tilde{c}_{ise}. \tag{4}$$

[38]This assumption is in line with families choosing school s in grade 9.

From equation (4) we can see that relative to the overall cost of switching school, $\tilde{c}_{ise}$, the value of college must be large.

5.3. Application score and equilibrium pool of accepted students

To characterize the equilibrium cutoff, AS^*, I need an assumption about how GPAs are distributed among students. Following Estevan, Gall, and Morin (2019), I assume students' GPA in schools H and L before any switching follow distributions $F_H(gpa)$ and $F_L(gpa)$ respectively, such that the aggregate distribution is given by:

$$F(gpa) = \mu_H \cdot F_H(gpa) + \mu_L \cdot F_L(gpa), \tag{5}$$

where μ_H and μ_L are the fraction of students in each school before switching happens.[39] Given equations (1) and (8), I can then define the distributions for AS in each school, which would be a transformation of the GPA distributions. Let $G_L(AS)$ and $G_H(AS)$ be the distributions for schools L and H respectively. Under this environment, two constraints characterize the application score in equilibrium and the pool of students accepted in college under any policy τ.

Constraint: Unique application score. Due to the centralized application system, the application score in equilibrium is the same for each school. Let gpa_L^* and gpa_H^* be the student's GPA that obtains an application score equal to the cutoff in equilibrium. Therefore:[40]

$$AS_L(gpa_L^*) = AS_H(gpa_H^*) = AS^*. \tag{6}$$

Constraint: College Capacity. Let d_H be equal to 1 if $AS_H(x) > AS_L(x)$ for a GPA of x. For any policy τ not changing the capacity constraint in college, the fraction of accepted

[39] Recall $\mu_L + \mu_H = 1$.

[40] Sub-index for GPA is added to make clear the marginal student admitted in college from each high school does not need to have the same GPA.

students in equilibrium must be equal to the number of seats available. Thus:

$$\mu_L \cdot \underbrace{(1 - G_L(AS_L(gpa_L^*)))}_{AS > AS^* \text{ in L}} + \mu_L \cdot (1 - d_H) \cdot \underbrace{[G_L(AS_L(gpa_L^*)) - G_L(AS_L(gpa_H^*))]}_{\text{movers from L to H}} +$$

(7)

$$+\mu_H \cdot \underbrace{(1 - G_H(AS_H(gpa_H^*)))}_{AS > AS^* \text{ in H}} + \mu_H \cdot d_H \cdot \underbrace{[G_H(AS_H(gpa_H^*)) - (G_H(AS_H(gpa_L^*))]}_{\text{movers from L to H}} = \underbrace{K.}_{\text{college capacity}}$$

5.3.1. Equilibrium

A perfect-information competitive equilibrium is a tuple $\{q = (q_L, q_H), AS^*\}$ that satisfies the following properties:

a. $q = (q_L, q_H)$ is the vector of student accepted in college from each school, which correspond to students for whom their applications score is higher than the cutoff in equilibrium.
b. AS^* is the unique *competitive market* application cutoff given the slots available in college, subject to students acceptance rates from school L and H, q_L and q_H, which are also function of the cutoff.

PROPOSITION 1. *In equilibrium, when the policy has not been implemented, students with $gpa_i \geq gpa_0^*$ are accepted into college from each school. Additionally, no one has incentives to switch schools, and each school fills a fraction of the available seats equal to the fraction of students they have times the mass of students who are above the application score AS_0^*.*

Recall before the policy the AS function was not affected by students' schools, and only by their GPA, which I assume is determined when they take the decision of switching or not schools. To see the intuition behind this proposition use constraints 5.3 and 5.3. By Constraint 5.3 we know $AS_L(gpa_L^*) = AS_H(gpa_H^*) = AS^*$. Using the deterministic function between GPA and AS before the policy in equation 1, we find that $gpa_L^* = gpa_H^*$. Finally, under the assumption that both distributions are equal, using Constraint 5.3 and the fact that students are not moving: $G_L(AS^*) = G_H(AS^*) = G(AS^*)$. For the formal proof, see Appendix A.

Now suppose the policy is implemented but students are not allowed to switch schools. Then the constraints will be:

$$AS_L(gpa_L^*) = AS_H(gpa_H^*) = AS_1^*,$$

and

$$1 - K = \mu_L \cdot G_L(AS_L(gpa_L^*) + \mu_H \cdot G_H(AS_H(gpa_H^*)).$$

Recall the deterministic non-linear function defining the application score after the policy is

$$AS_e(gpa_i) = \begin{cases} gpa_i + \theta & \text{if } \underline{g} \leq gpa_i < \underline{r}_e \\ (1+\alpha_e) \cdot gpa_i + \theta_e & \text{if } \underline{r}_e \leq gpa_i < \overline{r}_e \\ \overline{AS} & \text{if } \overline{r}_e \leq gpa_i \leq \overline{g}, \end{cases} \tag{8}$$

for $e \in \{H, L\}$.

PROPOSITION 2. *In equilibrium, when the policy is implemented, and students are not allowed to switch schools, as long as, $AS_1^* > \min\{AS(\underline{r}_L), AS(\underline{r}_H)\}$, schools H and L have different GPA cutoffs for being accepted into college, gpa_H^* and gpa_L^* respectively. As a consequence, the mass of accepted students increases in school with lower gpa^*, and decreases for the other school. Finally, AS^* goes up, when comparing with the outcome before the policy.*

For simplicity, assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L < \overline{r}_H$ as in Figure ??. Then using Constraint 5.3 and the fact that Equation 8 gives always a weakly higher application threshold for students in school L, $AS(gpa_i, L) \geq AS(gpa_i, H)$ for any given GPA, we have $gpa_L^* < gpa_H^*$. Now, using capacity constraint, we have:

$$\mu_L \cdot G(AS(gpa_L^*)) + \mu_H \cdot G(AS(gpa_H^*)) = 1 - K.$$

Since $gpa_L^* < gpa_H^*$, and assuming once more equal GPA distribution, it must be true that

$$G(AS(gpa_L^*)) < G(AS(gpa_H^*)),$$

given that $gpa_L^* < gpa_H^*$. Therefore, the fraction of people going to college from L is higher than from H. Finally, since $gpa_L^* < gpa_H^*$, but capacity constraint has not changed, it must be true that $AS_1^* > AS_0^*$. The formal proof can be found in Appendix A.

Finally, suppose the policy is implemented and students are allowed to switch schools, and the cost of switching is zero.

PROPOSITION 3. *In equilibrium, when the policy is implemented, and students are allowed to switch schools, as long as, $AS_2^* > \min\{AS(\underline{r}_L), AS(\underline{r}_H)\}$, schools have different GPA cutoffs for being accepted into college, gpa_H^* and gpa_L^*. After the policy implementation, the application score in equilibrium goes up. Finally, the impact of the policy, in terms of change in the pool of acceptances, depends on how costly is for students to switch.*

Proposition 3 follows a similar intuition than Proposition 2. The main difference is that now, due to the switchers, the application score goes up more, whenever the cost of switching, $\tilde{c}_{ijk}$, is strictly lower than the value of college (see proof in Appendix A). To see why the change in the pool of accepted students, one of the policy goals, depends on the cost of switching, suppose that cost is zero. Then, all the students who have a potential gain due to switching move. If we take the case shown in Figure **??**, we have that students with a GPA between $gpa_L^* = AS_L^{-1}(AS_2^*)$, and $gpa_H^* = AS_H^{-1}(AS_2^*)$ switch schools. If this is the case, then the effect of policy on the number of students accepted in college from school L is reversed, and there is no change in the pool of students accepted into college.

COROLLARY 1. *Let AS_0^* be the application score in equilibrium before the policy, AS_1^* the application score in equilibrium when the policy is implemented and students are not allowed to switch, and AS_2^* the resulted score after students relocate schools. Then*

$$AS_0^* \leq AS_1^* \leq AS_2^*.$$

5.4. Model's main predictions

The model provides me with clear predictions on high school students behavior regardless switching school that I can test in my setting.

First, only students in the middle of the school-specific GPA distribution have a positive application score change by switching school. The differences in the gain are coming from the non-linear function used to compare students in my setting. Second, students in high-quality school are more likely to have a positive score gain, this prediction is a result of high-quality school having higher thresholds in the application score's function. Finally, two conditions must hold for students with positive gain to be willing to switch schools: (i) their application scores' change has to be big enough to change their outcome from not being accepted to be accepted in college after switching schools, and (ii) they must value college more than the cost they incur by switching, which include how different they value high schools and the direct cost paid by switching. In the next two sections I present evidence in favor of these predictions.

6. Empirical analysis

6.1. Students' potential gain and treatment

This section presents the analysis of students' application score gains. The goal is to identify which students exhibit a *positive potential gain*—therefore they may have an incentive to switch schools under the RR policy—and to examine how this measure correlates with both student- and school-level characteristics.

I define *potential gain* (PG) for student i as the difference between the relative ranking score they would receive if they graduated from an alternative school e—one they were not attending at the beginning of 12th grade—and the score they would receive from graduating from their beginning-of-12th-grade school s. The *maximum potential gain* (MPG) is defined as the highest gain across all schools in the student's choice set:[41]

$$MPG_{i(s\rightarrow e^*)} = \max\{\Delta RR_{i(s\rightarrow 1)}, \Delta RR_{i(s\rightarrow 2)}, \ldots, \Delta RR_{i(s\rightarrow n)}\} \tag{9}$$

To compute the PG and MPG measures, I simulate the application score each student would obtain by graduating from every school in their choice set and compare these scores to the one they would receive at their actual school.[42] Given that the formula uses pre-determined variables (see section 4 for details), I can calculate MPG for any cohort, even when the policy was not in place.

For this exercise to be informative about students switching schools as a result of the gain created by the RR policy and its effects we should first, have that families do not migrate to a different school market due to the policy, and second, that the measurement error into the potential gain variable dos not suffer of non-classical measurement error problems. In the following two paragraphs, I outline three facts that help reducing potential endogeneity concerns.

First, in Chile students are not tied to public schools in their districts reducing the incentives for selective migration due to the policy change. Second, following a similar strategy than Chetty et al. (2014), I use students' primary school to calculate their school market, therefore anchoring students to a fixed, pre-policy location. Finally, using students' graduation high school for cohort graduating from 2012 onwards, I calculate the ranking score using my formula and compare it with the ranking score obtained from the administrative records.[43] Figure 8 present the distribution of the difference between the these two measures by years between 2012 and 2014.

Using each student's *maximum potential gain*, I categorize students into those with positive gain from switching schools ($MPG > 0$) and those with no gain ($MPG \leq 0$). Students with positive gain are part of the treated group ($gain = 1$), while students with no gain are

[41] Appendix D describes in detail how relevant markets (or choice set) were calculated for each student.

[42] A key part of this calculation is defining each student's relevant choice set. Following Neilson (2013); Allende (2019), I construct school markets using buffers with radii between 2 and 8 kilometers, centered on the student's primary school. See subsection 3.2 for details on data limitations.

[43] I can not do the sanity check for cohorts before 2012 since the relative ranking score did not exist before that year.

part of the control (*gain* = 0). On average, 56.7% of students in grade 12 in the country have at least one school in their relevant market that would increase their ranking score. Among students living in the metropolitan region (MR) 65% have a positive gain, on average. Figure A8 shows the percentage of students with positive gain by year while Figure A9 compares the distribution of MPG for students living in MR relative to other regions by year.

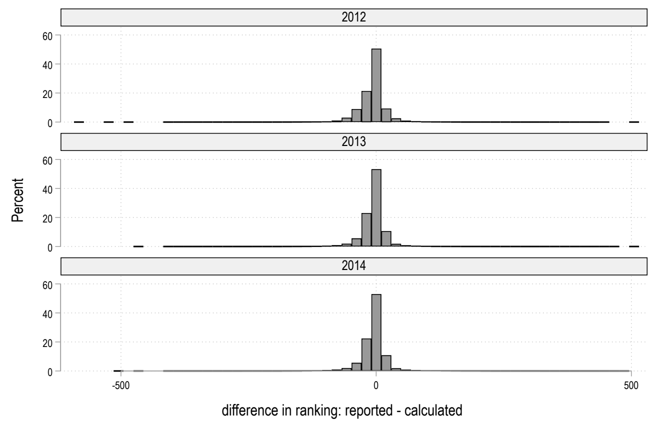


FIGURE 8. Difference between reported ranking score and calculated ranking score.

Note: This figure presents the distribution of the difference between the reported ranking in adminsitrative records from DEMRE, and the calculated ranking. The calculated ranking score was computed using the formula that the government implemented from 2012 until 2014.

Table 5 presents the results of comparing students' and schools' characteristics for the treatment group before and after the relative ranking policy was announced in 2014. As we can see in Panel A, there is no systematic difference in the likelihood of being in the treatment group by socioeconomic status or for students living in the metropolitan region. On the other hand, females and students whos parents have high aspirations for their educational attainment are 1 p.p. less likely to have positive gain in 2014, while students living in rural areas are 7 p.p. more likely to be in that group.[44]

[44]Less than 2.5% of students live in rural areas in Chile.

TABLE 5. Students characteristics & positive gain treatment

	Before (1)	After (2)	Difference (3)
Panel A: *Students' characteristics*			
Socio econonmic status			
Low-SES	-0.10***	-0.10***	0.00
	(0.00)	(0.01)	(0.00)
Medium-SES	[base]	[base]	[base]
High-SES	0.09***	0.09***	0.00
	(0.01)	(0.01)	(0.01)
Gender			
Male	[base]	[base]	[base]
Female	0.05***	0.03***	-0.01***
	(0.01)	(0.01)	(0.00)
Parents' aspirations			
Low asipirations	[base]	[base]	[base]
High asipirations	0.20***	0.18***	-0.01**
	(0.01)	(0.01)	(0.01)
Geographic area			
Lives in metropolitan region	0.16***	0.15***	-0.01
	(0.01)	(0.01)	(0.01)
Lives in rural area	-0.15***	-0.08***	0.07***
	(0.01)	(0.02)	(0.01)
Panel B: *Schools' characteristics*			
Type of financing			
Public school	-0.11***	-0.11***	0.01
	(0.01)	(0.01)	(0.01)
Voucher school	[base]	[base]	[base]
Private school	0.06***	0.02	-0.04***
	(0.02)	(0.02)	(0.01)
Quality			
Low quality (Q1)	[base]	[base]	[base]
Medium-Low quality (Q2)	0.04***	0.06***	0.02***
	(0.01)	(0.01)	(0.01)
Medium-High quality (Q3)	0.11***	0.12***	0.01
	(0.01)	(0.01)	(0.01)
High quality (Q4)	0.22***	0.23***	0.01
	(0.01)	(0.01)	(0.01)
Mean outcome: Pr(treatment)	0.53	0.58	

Note: $^{*}p < .10,^{**} < .05,^{***} p < 0.01$. Column 1 presents sample means and standard deviations from a pooled estimation for 2010-2013 cohorts. Column (2) presents the sample means and standard deviations from a pooled estimation for the 2014 cohorts. Column (3) reports the difference for each characteristic comparing before and afer. The coefficient for each characteristic comes from a OLS regression interacting the characteristic before and after. All the regressions are clustered at the school market level.

6.2. Students' switching decision

This section describes the main empirical strategy and results about students behavioral responses to increase their college application score after the RR's formula was made public in 2014 (see 4 for details).

To carry the analysis, I use a difference-in-difference design. I exploit two variations that determine a student's exposure to the policy: (i) whether students have a positive gain by switching schools and (ii) the year when they were in grade 12. The main assumptions to interpret the estimated coefficients as causal effects are the absence of previous trends in the outcome variable by groups compared in the regression, and the stability of the treatment variable (i.e., the stability on the likelihood of having a positive gain).

The equation to be estimated for the difference in difference analysis is the following:

$$switch_{istm} = \alpha + \delta_s + \delta_{gpa\_decile} + \delta_t + \psi \cdot gain_{ims} + \phi \cdot (gain_{ism} \cdot after_t) + \varepsilon_{istm} \tag{10}$$

where $switch_{istm}$ is equal to 1 if student i, attending school s at the beginning of grade 12 in year t, belonging to a school market m switched schools in grade 12 and 0 otherwise, $gain_{ism}$ is a dummy indicating whether the student has a positive gain by switching school in their relative ranking score, $after_t$ is a dummy for cohorts after 2013, α is a constant, δ_s is a beginning-of-grade-12 fixed effect, δ_m is a school market fixed effect

Equation 10 can be generalized to an event study to estimate the impact of having a gain year-by-year relatively to the year before the announcement (i.e., year 2013). Consider the following relationship between the relocation ($switch_{istm}$)

$$switch_{istm} = gain_{ism} \cdot \sum_{\substack{\tau=2010 \\ \tau\neq 2013}}^{2018} \beta_\tau 1\{t = \tau\} + \delta_t + \delta_s + \delta_{gpa\_decile} + \varepsilon_{istm} \tag{11}$$

$gain_{im}$ is equal to 1 if student has at least one school in their school market that would increase their relative ranking score. Each coefficient β_τ can be interpreted as an estimate of the impact of having a positive gain for a given cohort of 12 graders relatively to cohort in grade 12 during 2013. In other words, the parameters of interest are $\sum_{k \in K} \beta_\tau$ that represent the difference in the probability of switching school during grade 12 for students with and without fain, relatively to their difference in 2013.

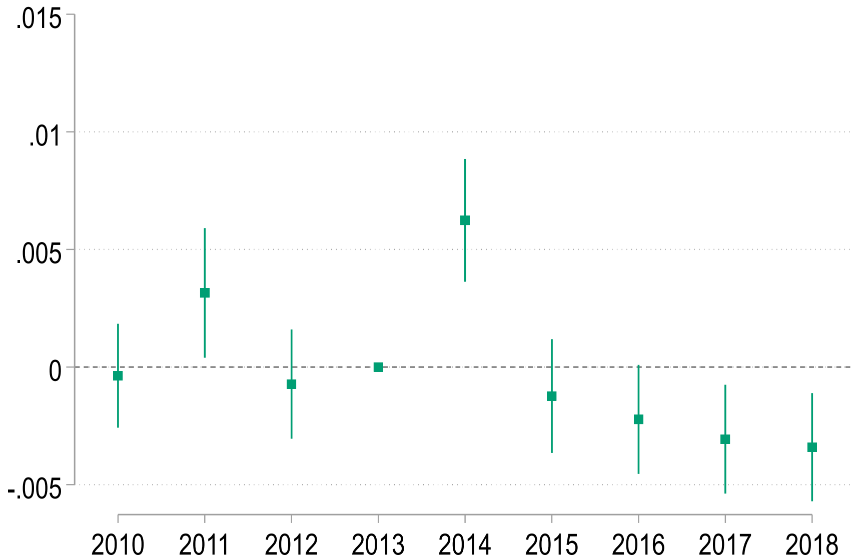


FIGURE 9. Event Study for relocation in grade 12 (2010-2018).

Figure 9 presents results for the full country. On average, the likelihood of switching schools for students with incentives increased by 1.5 percentage points (or 100%) with respect to students without incentives in 2014. Heterogeneity analysis in Figures 10, 11, 12, and 13 shows that the effect is driven by students in Santiago attending high-quality public schools with more advantageous backgrounds.

Overall, I find evidence that students switching schools in 2014 are most likely gaming the policy to increase their likelihood of being accepted in college. Students behaving strategically have parents who expect them to go to college ad they tend to have better socioeconomic backgrounds. In short, more advantaged students with parents with high aspirations are more likely to behave strategically in this context and switch schools during twelfth grade.

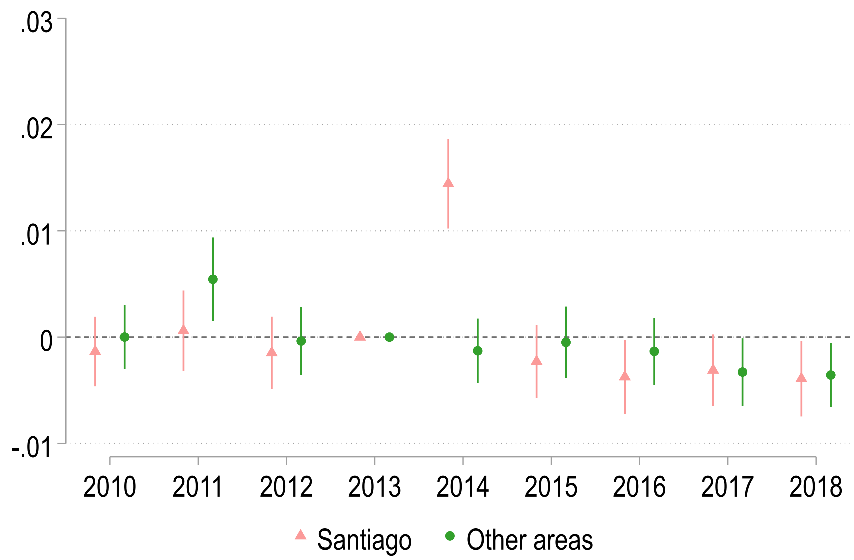


FIGURE 10. Event Study for relocation in grade 12, by area (2010-2018).

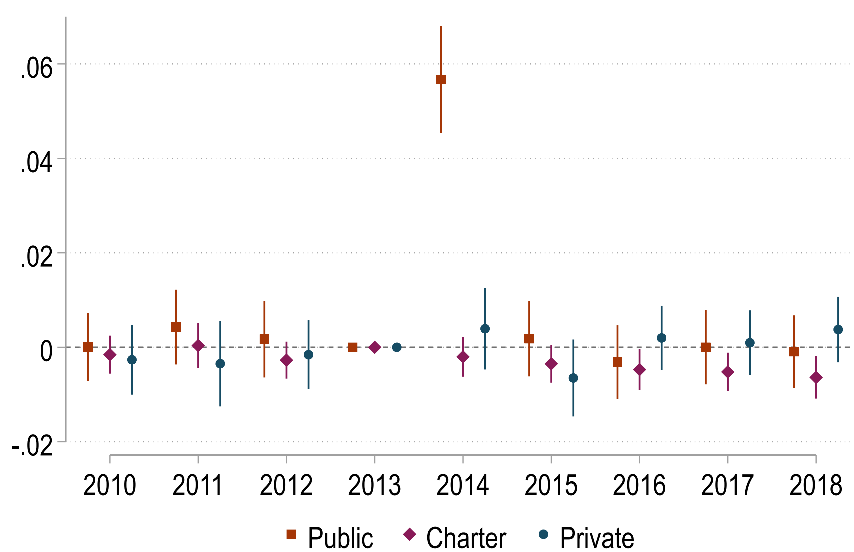


FIGURE 11. Event Study for relocation in 12th grade for students in public schools, Santiago only (2010-2018).

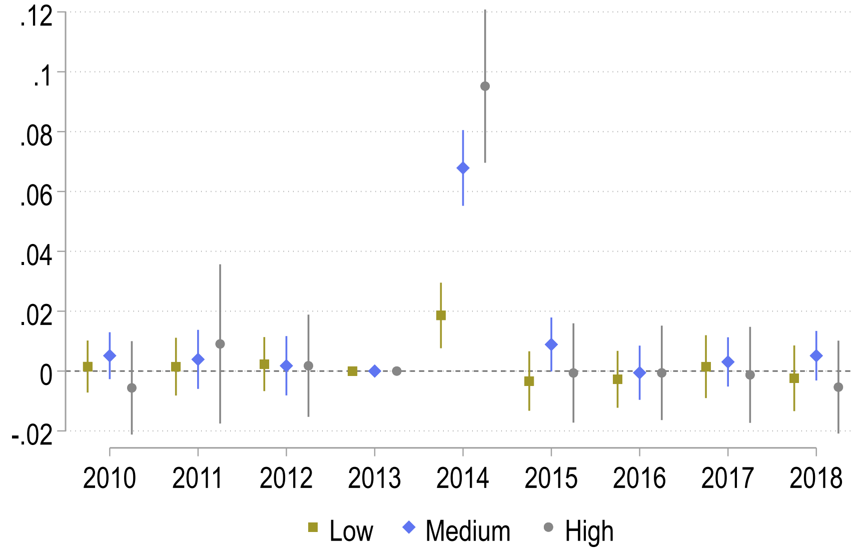


FIGURE 12. Event Study for relocation in 12th grade for students in public schools by SES, Santiago only (2010-2018).

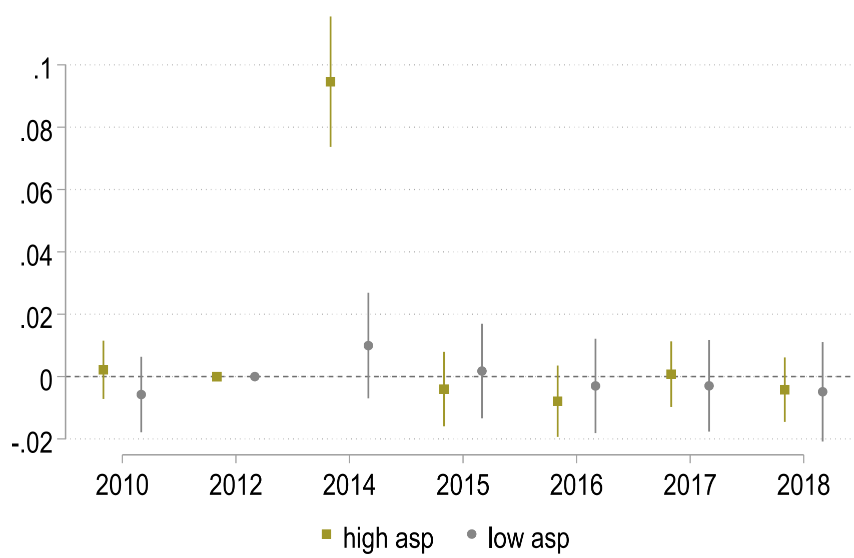


FIGURE 13. Event Study for relocation in 12th grade for students in public schools by parents' aspirations, Santiago only (2010-2018).

6.3. Students' enrollment and graduation outcomes

In this section, I look at changes in outcomes for students who switched schools, using the potential gain variable as an instrument. The outcome of interest is whether students' likelihood of enrolling in their first preference changed, given that they reacted strategically.

Figure 14 shows the event study results for the reduced form. On average, students with high potential gain are almost 1 pp more likely to be accepted on their most preferred major.

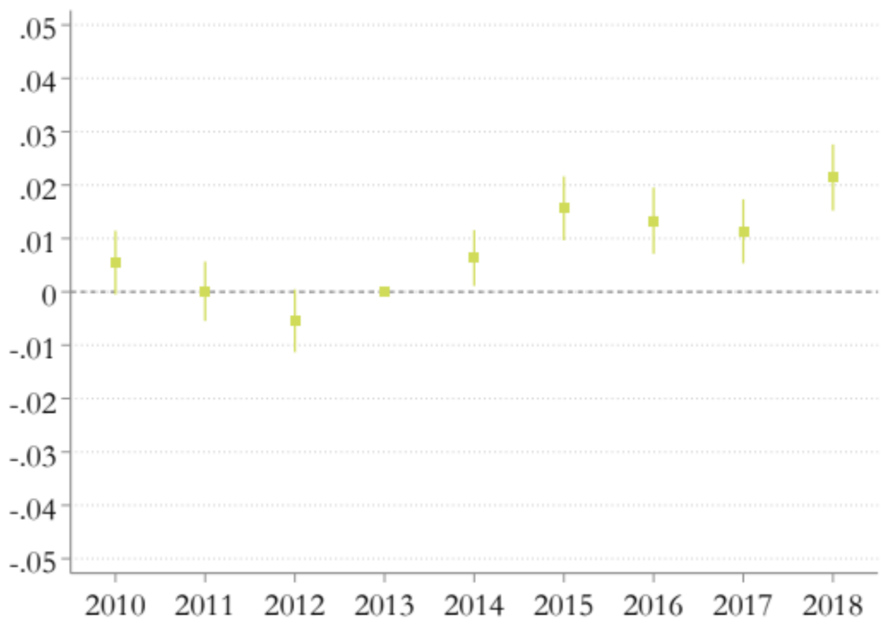


FIGURE 14. Event Study for reduce form effect results on probability of enrolling in their most preferred preference.

6.4. Discussion

Many affirmative action policies regarding higher education use high schools when defining the targeted groups. This strategy seems obvious when we take into consideration the connection between school quality and the type (public, charter, or private) that students from historically disadvantaged populations and communities attend.

An important problem with this type of *targeting* is the creation of incentives to game the policy. For those programs that are dependent on attending specific schools, school switching can then become a way for untargeted students to gain an unfair advantage.

In this paper, I show that school switching is an important unintended consequence that undermines the goal of this policy. Using students' graduation school as the treatment when evaluating the policy might *help* to inflate the effects of the policy. Figure 4 shows the effect of the RR policy considering the twelfth-grade starting school (first columns) and the graduated from school. The effect of this policy is clearly misleading (and overestimated) if we consider measuring it by the graduating school.

7. CONCLUSION

This paper presents evidence that changes in a centralized college admission system can significantly incentivize students' strategic behavior during high school, undermining the expected effects of the change. Specifically, I show that students game a Chilean affirmative action policy that uses a student's high school to target low socioeconomic students in college admissions. The endogenous relocation of students in response to the policy change reduces its effectiveness by 90%.

The results suggest more privileged students are more likely to switch schools to game the system, greatly increasing their probability of attending a selective college. These results are consistent with other research findings from the context of Texas Top Ten Percent law (Cullen, Long, and Reback 2013) and quotas in Brazil (Mello 2021). However, this previous research has not been able to estimate the effect of strategic behavior on the policy expected effect. To alleviate concerns about the results being actually driven by changes in the educational system from this change, I simulate the results of the policy using the same pool of applicants. For the characterization of students taking advantage of the policy, I use clear rule change and detailed data.

Understanding pre-college behavioral responses are key for effective policy design for access to college, especially given that unequal access to college is a first-order concern for policymakers. Students may react in unexpected ways, especially if it is fairly easy to assess the advantages. Thus more research is needed to improve our understanding of how these unintended consequences can undermine policies and how to try to account for those types of consequences.

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Appendix A. College Admission Process, Information Disclosure, and High School Students' Switching Decision

In Chile, before the end of 12th grade each year, students have access to the key information needed to navigate the college application process.[45] On the official website created by CRUCH for the national standardized test (PSU, now known as the Prueba de Acceso a la Educación Superior), students can find detailed information at various points throughout the year: a preliminary list of majors, the number of available slots, and the weights assigned to each admissions requirement (released at the end of May); an outline of the test content (early June); application rules, test registration procedures, and general application guidelines (late June); profiles of universities participating in the centralized system—including departments, statistics on enrollment and graduation, faculty credentials, and active research projects (early August); the final list of majors by university, with updated weights and admissions slots (late September to early October); test site locations (early November); information about scholarships, financial aid, and other benefits (late November); and enrollment instructions (early December).[46]

In the main text, I argue that students' decisions to switch schools in 2014—but not in earlier years—can be explained by the timing of information relevant to this decision. Here, I elaborate on this timeline in more detail. Although the RR policy was introduced at the end of the 2012 academic year and applied to the 2013 college admission process, its implementation had limited potential to influence students' switching behavior. In 2012, all universities participating in the centralized system incorporated the RR component by reducing the weight assigned to GPA by 10 percentage points. However, this change was announced in November, the final month of the academic year, making it too late to influence school transfer decisions.

In 2013, the weight assigned to RR increased substantially—on average, to 30 percent of the application score. However, this more consequential change was again only made

[45] See `https://demre.cl/calendario/` for the 2023 application timeline.
[46] See `https://demre.cl/calendario/` for the 2015 process timeline.

public in November,[47] rather than in the preliminary information typically released in June. As a result, 12th-grade students in 2013 also lacked the timely information needed to make a strategic school switch. Therefore, the 2014 cohort—students who began 12th grade in early 2014—were the first to have full knowledge of the RR policy, its implementation, and the details of its calculation early enough in the academic year to adjust their behavior accordingly.

Appendix B. Model Derivations and Proofs

PROOF. Proposition 1. To show this proposition, I need to show that $gpa_H^* = gpa_L^* = gpa_0^*$ before the implementation of the policy. The rest of the proposition follows from it.

By contradiction, suppose $gpa_H^* \neq gpa_L^*$. We know by Equation 1 that the college application score for a student applying from school H with GPA equal to gpa_H^* is

$$AS_H^* = gpa_H^* + \theta,$$

similarly, for a student applying from school L with GPA equal to gpa_L^*

$$AS_L^* = gpa_L^* + \theta,$$

Now, by the unique application score constraint we have

$$\begin{aligned} AS_H^* &= AS_L^* \\ gpa_H^* + \theta &= gpa_L^* + \theta \\ gpa_H^* + \theta &= gpa_L^* + \theta \\ gpa_H^* &= gpa_L^*, \end{aligned}$$

which contradicts our assumption that $gpa_H^* \neq gpa_L^*$.

Now, since AS does not depend on where student graduated, there are not incentives

[47] For details, see `https://demre.cl/psu/publicaciones/listado-2014`.

to relocate. Finally, from the capacity constraint we have

$$\mu_H G_H(AS_0^*) + \mu_L G_L(AS_0^*) = 1 - K.$$

Therefore, the proportion of students going to college from school H is

$$\underbrace{\mu_H}_{\text{Fraction of the population in school H}} \cdot \underbrace{(1 - G_H(AS_0^*))}_{\text{Mass of students with GPA higher than } gpa_H^*}.$$

Similarly for school L.

□

PROOF. Proposition 2.

Assume that $gpa_H^* = gpa_L^*$. Since $AS_1^* > \min\{AS(\underline{r}_L), AS(\underline{r}_H)\}$, under the new policy for any gpa we have

$$AS_L(gpa) \neq AS_H(gpa),$$

as long as $\underline{r}_L \neq \underline{r}_H$ or $\overline{r}_L \neq \overline{r}_H$. This come directly from Equation 8.

Assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L \leq \overline{r}_H$, then for any student with $gpa \in (\underline{r}_L, \overline{r}_H)$ the application score graduating from school L is higher than when they graduate from school H, $AS_L(gpa) > AS_H(gpa)$. Now, using Constraint 5.3, we know that in equilibrium

$$AS_L(gpa_L^*) = AS_H(gpa_H^*).$$

Let AS_1^* be the unique cutoff in equilibrium after the policy is implemented but students are not allowed to switch. Since $AS_1^* = AS_L(gpa_L^*)$, then $gpa_L^* = AS_L^{-1}(AS_1^*)$, and $gpa_H^* = AS_H^{-1}(AS_1^*)$. Therefore $gpa_L^* < gpa_H^*$ when $AS_L(gpa) > AS_H(gpa)$.

Using Constraint 5.3 and imposing no switching, we have

$$\mu_H G_H(AS_1^*) + \mu_L G_L(AS_1^*) = 1 - K,$$

Under no changes in college capacity constraint, it must also be true that:

$$\mu_H G_H(AS_1^*) + \mu_L G_L(AS_1^*) = \mu_H G_H(AS_0^*) + \mu_L G_L(AS_0^*)$$

$$\mu_L \underbrace{\left[G_L(AS_1^*) - G_L(AS_0^*)\right]}_{\text{change in mass of students with } gpa > AS^* \text{ in school L}} = \mu_H \underbrace{\left[G_H(AS_0^*) - G_H(AS_1^*)\right]}_{\text{change in mass of students with } gpa > AS^* \text{ in school H}}$$

Which implies that the change in number of accepted (displaced) students from school L must be equal to the number of displaced (accepted) students from school H.

$$\mu_L\left[G_L(AS_L(gpa_{L,1}^*)) - G_L(AS_L(gpa_0^*))\right] = \mu_H\left[G_H(AS_H(gpa_0^*)) - G_H(AS_H(gpa_{H,1}^*))\right]$$
$$\mu_L\left[G_L(AS_L(gpa_{L,1}^*)) - G_L(AS(gpa_0^*))\right] = \mu_H\left[G_H(AS(gpa_0^*)) - G_H(AS_H(gpa_{H,1}^*))\right]$$

Because $gpa_{L,1}^* \neq gpa_{H,1}^*$, it must be true that one school gain and the other lost in terms of acceptance rate. If $gpa_L^* < gpa_H^*$, school L gains and school H lost. Because students are not allowed to move, then $\mu_L\left[G_L(AS_L(gpa_{L,1}^*)) - G_L(AS(gpa_0^*))\right]$ and $\mu_H\left[G_H(AS(gpa_0^*)) - G_H(AS_H(gpa_{H,1}^*))\right]$ represents the change in the composition of accepted students into college in terms of school of origin.

Now assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L > \overline{r}_H$. Then for any student with $gpa \in (\underline{r}_L, r^*)$ the application score graduating from school L is higher than when they graduate from school H, $AS_L(gpa) > AS_H(gpa)$. When $gpa \in (r^*, \overline{gpa}_L)$, the application score in school L is lower than in school H,$AS_L(gpa) < AS_H(gpa)$ (see Figure **??**). Now, using Constraint 5.3, we know that in equilibrium

$$AS_L(gpa_L^*) = AS_H(gpa_H^*).$$

Let AS_1^* be the unique cutoff in equilibrium after the policy is implemented but students are not allowed to switch. Since $AS_1^* = AS_L(gpa_L^*)$, then $gpa_L^* = AS_L^{-1}(AS_1^*)$, and $gpa_H^* = AS_H^{-1}(AS_1^*)$. Therefore $gpa_L^* < gpa_H^*$ when $AS_L(gpa) > AS_H(gpa)$, and $gpa_L^* > gpa_H^*$ when $AS_L(gpa) < AS_H(gpa)$.

Similarly than before, from Constraint 5.3 we have

$$\mu_L\left[G_L(AS_L(gpa^*_{L,1})) - G_L(AS_L(gpa^*_0))\right] = \mu_H\left[G_H(AS_H(gpa^*_0)) - G_H(AS_H(gpa^*_{H,1}))\right]$$
$$\mu_L\left[G_L(AS_L(gpa^*_{L,1})) - G_L(AS(gpa^*_0))\right] = \mu_H\left[G_H(AS(gpa^*_0)) - G_H(AS_H(gpa^*_{H,1}))\right]$$

In this case, the fraction of accepted students from school L increased when $AS^*_1 \in (\underline{r}_L, r^*)$, and decreased when $AS^*_1 > r^*$

$\square$

PROOF. Proposition 3. The first part of this proposition follows from Proposition 2. Next, I need to show that the impact of the policy in the pool of accepted students into college depends on how costly is to switch.

Recall from Proposition 2, that if students are not allowed to switch, then the policy completely passes through. The effect is the same if for all students, we have.

$$U_c < \tilde{c}_{ijk}$$

Now, suppose the cost of switching is zero, $\tilde{c}_{ijk} = 0$, then all students with positive utility change, $\Delta V_{i(k)} > 0$, relocate schools. By unique threshold constraint we know that in equilibrium

$$AS_L(gpa^*_L) = AS_H(gpa^*_H),$$

with $AS_L(gpa) \neq AS_H(gpa)$ for any given GPA. From Constraint 5.3:

$$\begin{aligned} 1 - K =&\mu_L \cdot G_L(AS_L(gpa^*_L)) + \mu_H \cdot G_H(AS_H(gpa^*_H)) \\ &+ \mu_L \cdot (1 - d_H) \cdot [G_L(AS_L(gpa^*_H)) - G_L(AS_L(gpa^*_L))] \\ &+ \mu_H \cdot d_H \cdot [(G_H(AS_H(gpa^*_L)) - G_H(AS_H(gpa^*_H))] \end{aligned}$$

Notice that one of the two last lines are *effective* for any combination of application score in school H and L.[48] Suppose $d_H = 1$, then the capacity constraint is

$$1 - K = \mu_L \cdot G_L(AS_L(gpa_L^*)) + \mu_H \cdot G_H(AS_H(gpa_H^*)) + \mu_H \cdot [G_H(AS_H(gpa_L^*)) - G_H(AS_H(gpa_H^*))]$$

Simplifying a little:

$$1 - K = \mu_L \cdot G_L(AS_L(gpa_L^*)) + \mu_H \cdot G_H(AS_H(gpa_L^*))$$

Using the result from before the policy, as we did before,

$$\mu_H G_H(AS_0^*) + \mu_L G_L(AS_0^*) = \mu_L \cdot G_L(AS_L(gpa_L^*)) + \mu_H \cdot G_H(AS_H(gpa_L^*))$$

Which is true when $gpa_0^* = gpa_L^*$, therefore the pool of students accepted into college did not change.

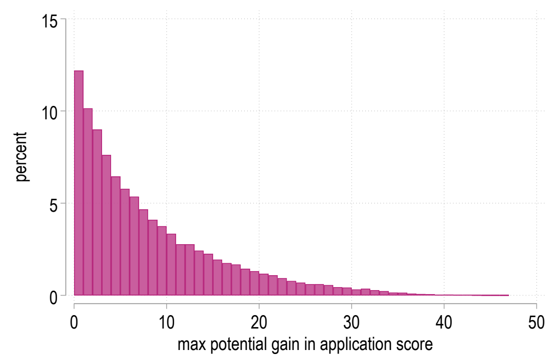
Finally, suppose a fraction q of students with a potential gain in switching, have a cost of switching higher than the value of college. Then only that fraction of students switch schools, and therefore the pool of accepted students into college change in a ratio equal to $1 - q$.

$\square$

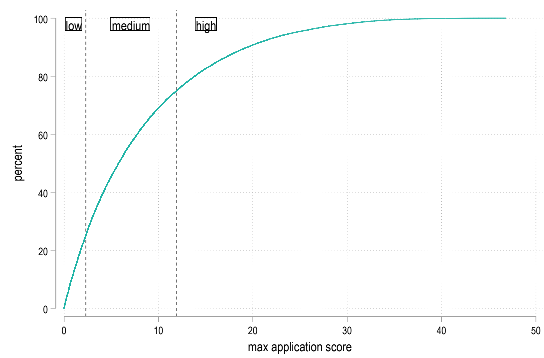
[48] It is not possible to have $AS_L(x) > AS_H(x)$ for a value x and simultaneously $AS_L(x) < AS_H(x)$.

Appendix C. Students relevant educational choice set

Recall a key component to calculate studensts' potential gain is their choice set. My primary analysis uses a 4-kilometer buffer. Figure A1 summarizes the distribution of *potential score gain* and its empirical cumulative distribution in 2010-2013. Conditional of having a gain greater than one point, 1/3 of students have less than a 2.5-point potential score gain (*low-gain*) another 1/3 of students has a potential score gain higher than 11 points (*high-gain*). As a sensitivity analysis, Figure **??** presents the *potential gain* distribution for 2- to 8-kilometer buffer using student's primary school as the center.



A. Distribution



B. Empirical CDF

FIGURE A1. Potential score gain, 4 km buffer (2010-2013).

Note: .

Appendix D. Additional tables and figures

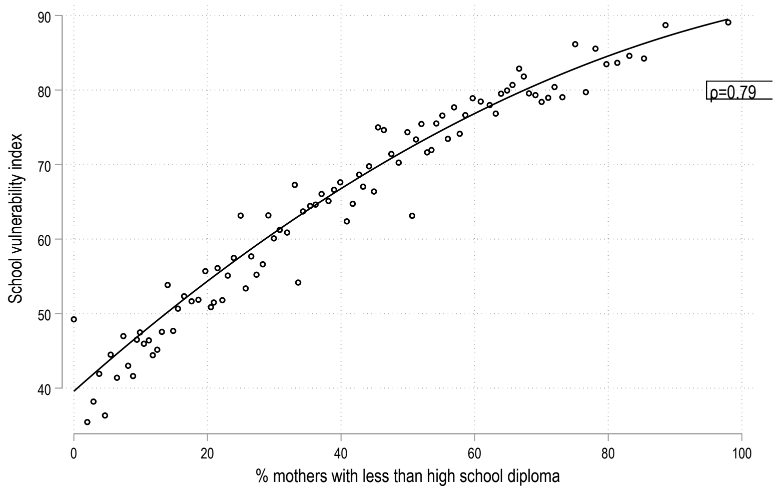


FIGURE A2. School vulnerability index & students SES

Note: This figure presents the association between the percent of students with mother's education lower than high school ($< HS$) and their school's vulnerability index (IVM). Each dot represents the average percent of students among the schools located in the n^{th} percentile of the IVM in 2010.

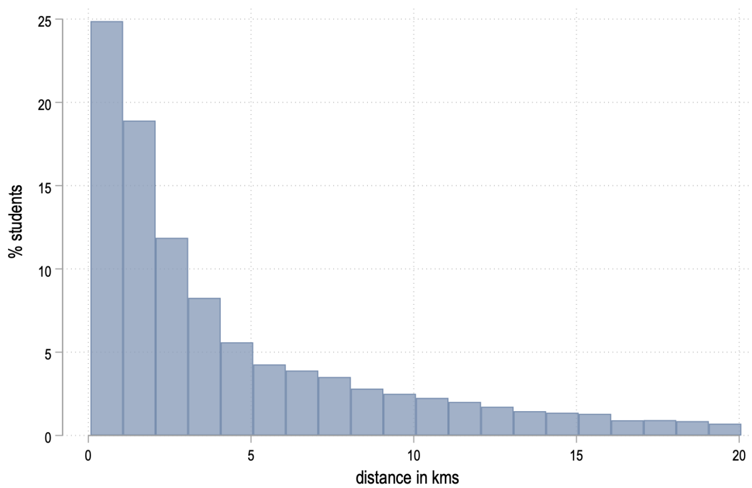


FIGURE A3. Distribution of distance to school

Note: This figure presents the distribution of students' high school distance.

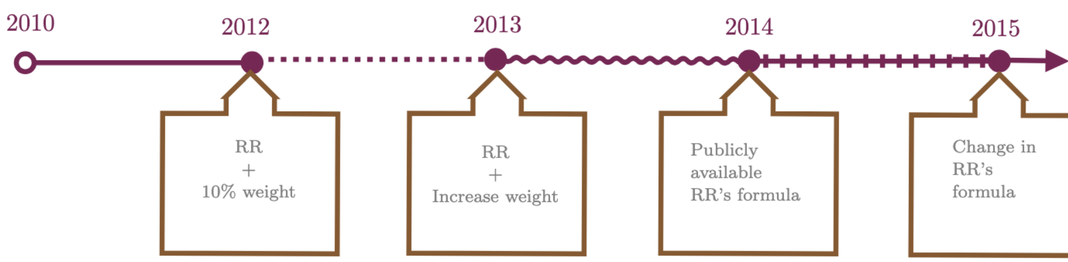
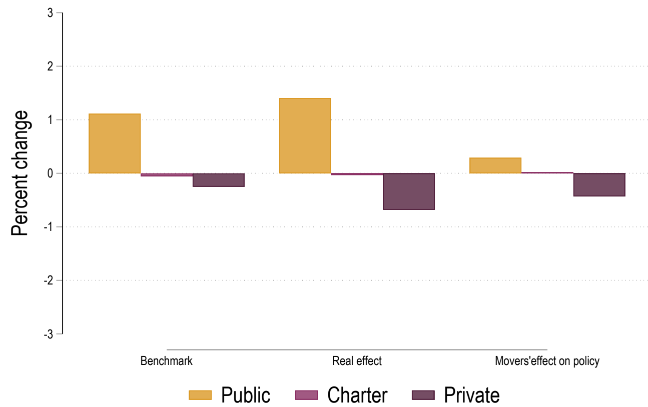


FIGURE A4. Relative ranking policy's timeline

Notes: This timeline presents the changes made to the RR policy in different years. In 2012 they incorporated the policy with a weight of ten percent. This weight was subtracted from NEM's weight. In 2013 universities increased the weight associated to the RR. This new increase was coming either from NEM or PSU's weights, depending of the university. In 2014 the entity in charge of the centralized admission system made all the information publicly available for students, there was no change in weights from 2013 this year. Finally, in 2015, they readjusted the formula of the RR component.



A. Acceptance rate in *any* university

B. Acceptance rate in *tier 1* universities

FIGURE A5. Policy effects in cohort applying to college in 2014 by type of school.

Note: This figure depicts the percentage change in the number of students accepted in college by type of school. The denominator in the percentage is the number of students accepted into each category without the policy. Figure (a) presents the changes in the rate of acceptance in any university. Figure (b) presents the policy effect for tier 1 colleges (top-2 universities).

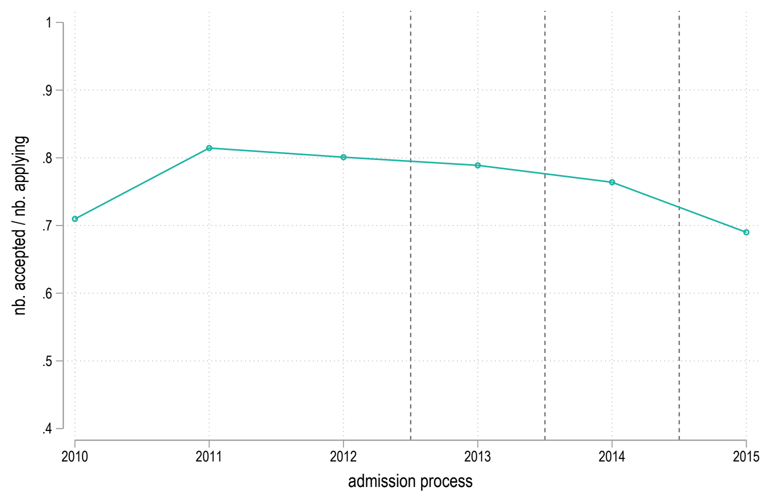


FIGURE A6. Average number of slots in the system (2010-2015)

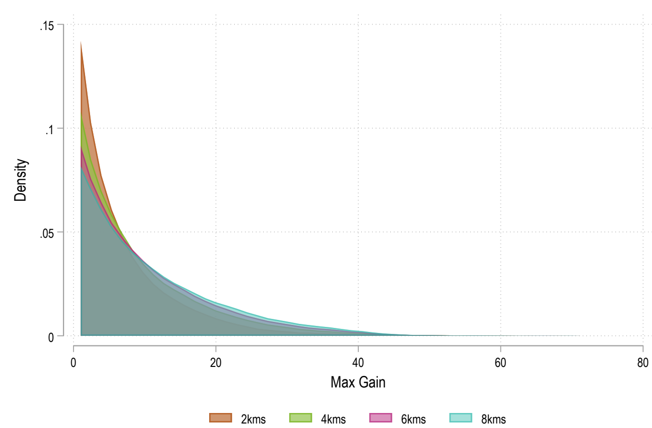


FIGURE A7. Distribution student's maximum potential gain (2010-2013)

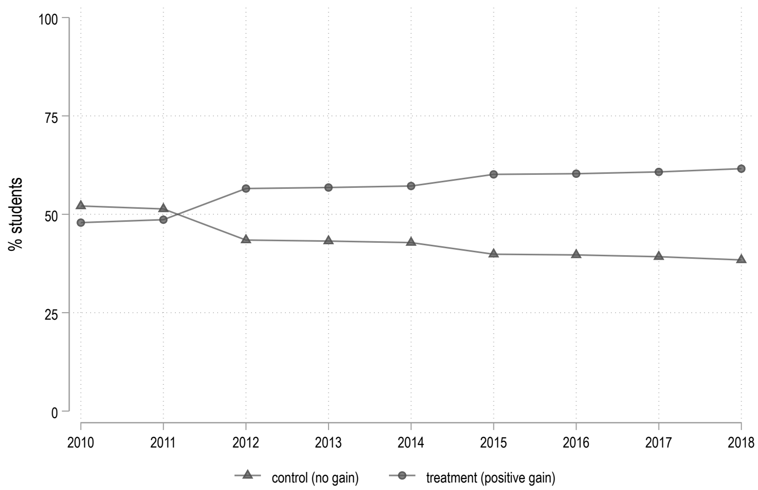


FIGURE A8. Ratio students with positive potential gain.

Note: This figure presents the percent of students with positive potential gain (dots) and no potential gain (triangles) in their choice set defined as a 2-km buffer with students' primary schools between 2010 and 2018.

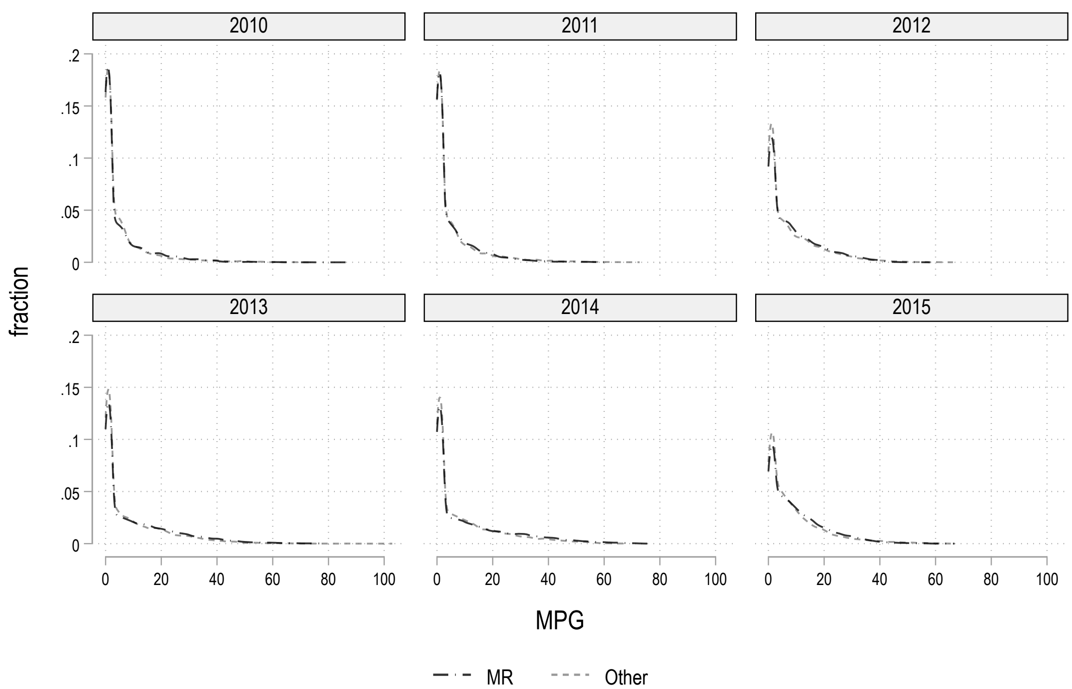


FIGURE A9. Potential gain's distribution by year and area.

Note: This figure presents distribution of MPG by year and area between 2010 and 2015.