Strategic Responses to College Admission Policies: Evidence from Chile

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This paper shows that the intended effects of a common class of progressive college admission policies can be weakened by strategic pre-college behavior. Exploiting the public disclosure of a relative-ranking–based affirmative action policy in Chile and combining it with comprehensive administrative data covering all college applicants nationwide, I find that students with scope to benefit strategically are about 50 percent more likely to transfer high schools during twelfth grade. While these students are more likely to enroll in highly selective college majors, they are less likely to graduate on time. Using simulation-based counterfactuals, I show that strategic school switching substantially attenuates the policy's distributional impact, reducing admissions of disadvantaged students to the most selective universities by approximately 30 percent.

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1. INTRODUCTION

College attendance is a key channel for upward mobility across developed and developing countries (Chetty, Deming, and Friedman 2025; Barrios Fernández, Neilson, and Zimmerman 2024). At the same time, access to higher education—particularly at selective institutions—remains highly unequal, with a disproportionate share of college seats going to students from the highest income quantiles (Chetty et al. 2020; Michelman, Price, and Zimmerman 2022; Zimmerman 2019). In Latin America, for instance, only 16 percent of students enrolled in tertiary education in 2023 came from the poorest income quintile—nearly 30 percentage points fewer than those from the wealthiest quintile (Arias Ortiz et al. 2024). In response to these disparities, governments around the world have implemented a wide range of policies aimed at expanding access to higher education for students from historically disadvantaged backgrounds.[1]

Among these interventions, policies that grant preferential treatment to certain groups in admissions are both widespread and highly contested, in the United States and internationally (Arcidiacono, Lovenheim, and Zhu 2015; Neilson 2019).[2] These policies are explicitly designed to promote equity by reallocating admission opportunities toward underrepresented students. However, because they rely on mechanical eligibility rules—often tied to observable characteristics such as high school attended—they may also create incentives for students who are not directly targeted to adjust their pre-college choices in order to benefit from the policy, even in the absence of changes in effort or academic investment. Such purely strategic responses have the potential to weaken the policies' intended distributional effects by reshaping which students ultimately benefit

[1] 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 information policies to reduce uncertainty around college returns (Dynarski et al. 2021). See Deming and Dynarski (2010) for a comprehensive review.

[2] 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) and direct access for high-performing low-income students (Tincani et al. 2021).

from the intervention.

This paper shows that the intended effects of a common class of progressive college admission policies can be weakened when high school seniors respond strategically by switching schools. Although students who switch schools increase their chances of enrolling in selective colleges, these strategic relocations reduce the policy's effectiveness by displacing students from low socioeconomic backgrounds who would otherwise have been admitted to elite universities. I exploit a natural experiment generated by the public disclosure of a relative-ranking criterion in Chile's centralized college admission system. This information release affected students in two key ways: it made salient that college application scores depended on students' relative performance within high schools, and it created incentives to transfer *at the last moment* to schools where students could improve their relative ranking—and thus their perceived admission chances—without changing academic effort or preparedness.

In late 2013, Chile's centralized college admission system publicly disclosed the formula for the Relative Ranking (RR) component, one of three elements of the application score. The RR score transforms a student's GPA into an admissions bonus based on their rank relative to the previous three graduating cohorts at their school. Although RR was introduced in 2012, the nonlinear mapping between GPA and RR scores became public only with this disclosure. While intended to expand access for high-achieving students in weaker schools, the formula implies that, for a given GPA, graduating from a school with lower historical thresholds yields a higher admissions score.

Chile provides an especially well-suited setting for studying pre-college strategic responses and their implications for policy effectiveness for three main reasons. First, a central challenge in this literature is the lack of data linking students' pre-college decisions, school trajectories, and college applications (Bodoh-Creed and Hickman 2018). Chile overcomes this limitation through rich administrative records that track students throughout their educational careers and the centralized college application process. Second, Chile's centralized admission system operates under transparent and uniform rules, with students submitting ranked preferences over specific degree programs,[3] which allows observation of system-wide student–major matches and the simulation of counterfactual allocations.[4] Finally, Chile permits high school transfers up to two months before the academic year ends, creating scope for strategic school switching in response to changes in the college admission system.[5]

By linking multiple administrative records, I construct a unique dataset that tracks cohorts of students graduating from high school between 2010 and 2018. These data allow me to identify whether students transfer schools in twelfth grade—distinguishing between transfers at the beginning of the academic year and those occurring during the year—and to compute the relative ranking score each student would receive if they graduated from any school within their relevant choice set. Using this information, I classify students as treated if they have a positive potential gain from switching schools and as controls otherwise.[6] I also construct a measure of socioeconomic status (SES) using information reported in tenth- and twelfth-grade surveys. This dataset is used throughout the analysis to estimate the causal effect of the policy on twelfth-grade school switching and on subsequent college admission and enrollment outcomes.

I divide the analysis into three parts. First, I develop a simple model in which students decide whether to transfer high schools, taking selective college admission cutoffs as given. The model clarifies when a school-based admissions rule alters the composition of admitted students and when its effects are attenuated by strategic relocation. The policy is more effective at increasing acceptance rates for students from low-performing schools when school switching is costly.[7] Moreover, because the RR formula is nonlinear, incentives to switch are concentrated among students in the middle of the GPA distribution at high-performing schools, where higher historical thresholds generate larger potential gains from graduating elsewhere.

[3] For example, Economics at the University of Chile.

[4] Centralized admission systems have become increasingly common worldwide (Neilson 2019), enhancing the external relevance of this setting.

[5] In Chile, students may enroll in public, voucher, or private schools in any county.

[6] Given the RR formula, I can calculate potential gains for all cohorts in my sample.

[7] Low-performing schools are defined as those with historically lower average GPAs.

The second part of the paper estimates the causal effect of the information release on strategic school switching during twelfth grade and on subsequent college outcomes. I begin by analyzing how the public disclosure of the Relative Ranking (RR) policy formula affected students' high school transfer decisions. Exploiting variation in students' potential gains from the policy and using a difference-in-differences event-study design, I show that the release of information led to a meaningful increase in school transfers during twelfth grade. Students who stood to gain from switching schools were 1.2 percentage points more likely to transfer in 2014 relative to the pre-policy period, corresponding to a 54 percent increase over the pre-disclosure mean.

I then examine geographic heterogeneity in these responses. When separating students in Santiago from those in the rest of the country, I find that the effect is entirely driven by students residing in the metropolitan area. Among students living in Santiago, having a positive potential gain increases the likelihood of switching schools by 2.4 percentage points, a 140 percent increase relative to the pre-policy mean. Monthly data further show that these transfers occur disproportionately toward the end of the academic year—when strategic switching is most valuable and least costly.

After establishing that the average effect is driven by students in Santiago, I investigate heterogeneity across students and schools within the metropolitan area. I find that responses are concentrated among more advantaged students. In particular, students whose parents held high educational aspirations were 3.2 percentage points more likely to transfer schools following the information release, and students attending high-performing high schools were 4.5 percentage points more likely to switch during twelfth grade.

Finally, I estimate the impact of the RR policy disclosure on students' postsecondary outcomes. Focusing on students living in Santiago, I find that having a positive potential gain does not increase overall admission to or enrollment in universities participating in the centralized admission system. Instead, students with positive gains are 1.4 percentage points more likely to enroll in highly selective programs and 2.6 percentage points less likely to graduate on time, suggesting that strategic school switching increased access to more selective programs but came at the cost of slower academic progression.

In the last part of the paper, I study the policy's intended distributional effects by exploiting the structure of the application score formula and the centralized college–student matching algorithm. To evaluate policy effectiveness, I simulate student–major assignments under a counterfactual scenario in which no student switches schools during twelfth grade and compare these allocations to the observed matches that incorporate strategic switching. Focusing on school performance—a dimension explicitly emphasized by policymakers when introducing the reform—I find that, under the current policy, students from low socioeconomic backgrounds are 3.5 percent more likely to be admitted to selective colleges. In the absence of strategic switching, however, this effect would have reached 5 percent, implying that strategic responses reduced the policy's potential effectiveness by more than 30 percent.

This study makes two main contributions. First, by analyzing pre-college strategic responses, their long-term consequences for students, and the distributional effects of pre-college responses I contribute to a growing empirical literature identified unintended consequences of educational policies. Previuous reserach has found that college admission policies affect students pre-college outcomes such as effort (Grau 2018; Bodoh-Creed and Hickman 2018; Tincani et al. 2021; González and Johnson 2018), time spent studying (Caldwell 2010), high school attendance (Akhtari, Bau, and Laliberté 2024), high school dropout rates (Cáceres-Delpiano, Giolito, and Castillo 2018), results in high-stakes exam performance (Antonovics and Backes 2014; Bleemer 2021; Akhtari, Bau, and Laliberté 2024; Laajaj, Moya, and Sánchez 2022), racial segregation in high schools (Estevan, Gall, and Morin 2019), and school choice (Cullen, Long, and Reback 2013; Mello 2021; Estevan, Gall, and Morin 2019). In my analysis, I show that students are more likely to respond strategically by switching schools when college admission policies include school-specific relative performance and calculate the distributional effects that strategic behavior has on the overall admission system, an equilibrium effect that previous literature could not calculate.

My results also speak 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; Bertrand, Hanna, and Mullainathan 2010). 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. I complement this body of work by focusing on one possible student pre-college strategic behavior that college admission policies can create: strategic high school transfer, students' subsequent outcomes, and transfers impacts on the policy effectiveness

Second, this paper contributes to the literature on relative grading and rank-based incentives by showing that school-specific performance comparisons can distort pre-college choices when admission stakes are high. Prior research documents that students' ordinal rank affects peer interactions and educational choices (Calsamiglia and Loviglio 2019), college attendance (Elsner and Isphording 2017; Diamond and Persson 2016; Rangvid 2015), and later earnings (Diamond and Persson 2016). I contribute to this literature by showing that when college admission scores depend on relative performance within high school, students in higher-performing schools may receive lower application scores despite identical GPAs. This feature creates incentives to transfer to lower-performing schools to improve admission prospects.

The rest of the paper is organized as follows. Section 2 describes the institutional setting. Section 3 introduces a stylized model to understand the incentives for switching schools and their equilibrium effects. Section 4 presents the data, descriptive statistics, and main variables construction. Section 5 outlines the identification strategies. Section 6 presents the empirical results. Section 7 presents the counterfactual analysis. Section 8 concludes.

2. CONTEXT: FROM SECONDARY TO HIGHER EDUCATION IN CHILE

Chile is a middle-income country with persistently high income and educational inequality.[8] Narayan et al. (2018) ranks it 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

Chile has the highest secondary education graduation rate in Latin America, with relatively little variation across socioeconomic groups. In 2022, 89% of young people completed upper secondary education—85% among those in the lowest income quintile and 95% among those in the highest (?). Yet, students from low socioeconomic backgrounds attend schools with significantly lower academic performance. Figure 1 presents the relationship between schools' ranking and the percentage of students receiving free lunch in 2010.[9] The figure shows a strong positive correlation ($\rho = 0.79$), indicating that lower-ranked schools—those with weaker average academic performance—tend to serve a larger proportion of socioeconomically disadvantaged students.

In contrast to the United States, Chile's education system allows parents to enroll their children in any K–12 school, irrespective of residential location, resulting in one of the most extensive school-choice systems globally. This high degree of choice applies not only to private schools—which served roughly 7% of high school students in 2010—but also to public and voucher-subsidized schools, which together account for about 93% of all high school students nationwide.[10] Table A1 shows that between 20% and 40% of students attend a school located outside their county of residence, with similar patterns across sectors. However, average scores on the national college admission test differ

[8] 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.

[9] School ranking was calculated as the average score on a standardized test taken by 10th-grade students in 2010.

[10] The share of high school students enrolled in private schools increased by 0.8 percentage points (about 11%) between 2010 and 2023.

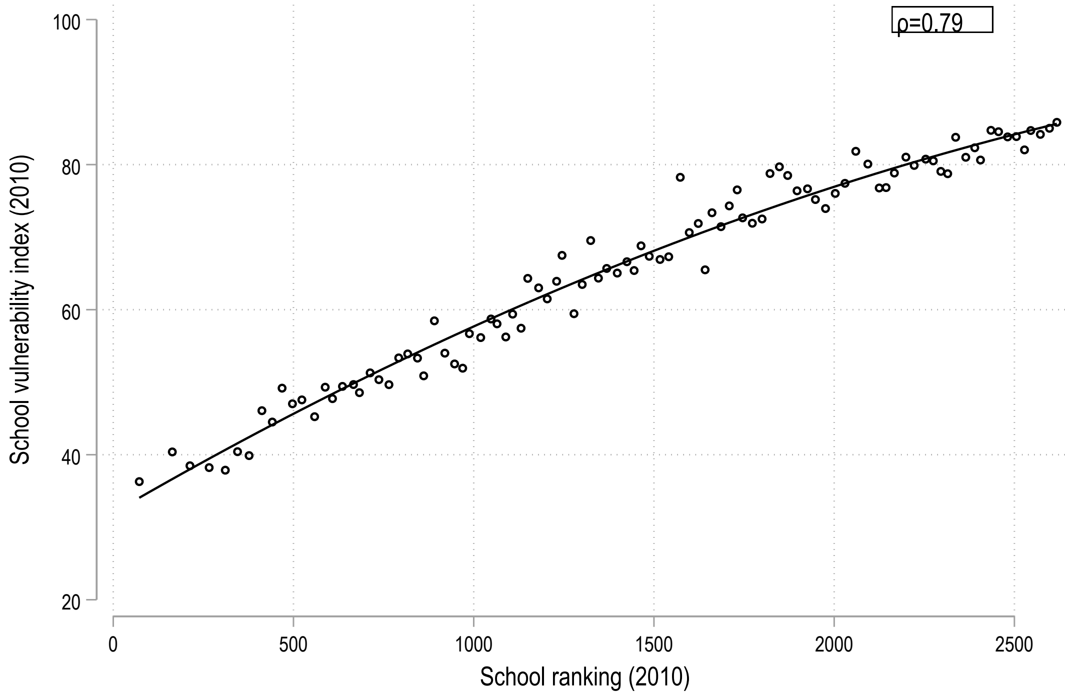


FIGURE 1. School Vulnerability Index & School Ranking

Note: This figure presents the associations between school ranking (x-axis) measured using the average on 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.

systematically across school types.

Differences in school performance help explain part of the large gap in tertiary education attendance: about 70% of individuals from the highest income quintile enroll in some form of tertiary education, compared with only 25% from the lowest quintile.[11] The link between students' socioeconomic status, school quality, and access to higher education has been a central concern of education policy reform 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.[12] Advocates for reform argued that students from low-quality schools face significantly lower chances of

[11]The net attendance rate indicator measures the percentage of people effectively attending tertiary education over the population that should be attending according to their age (**?**).

[12]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`.

attending college—regardless of their individual ability or academic performance—due to 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. College Application System

For the academic year 2013, all public universities and 16 of the 35 private universities in Chile admit students through a centralized admissions system. Since 2012, each applicant's Admission Score (AS) is a weighted sum of three components—the national standardized test (PSU), the student's high school GPA, and the Relative Ranking (RR)—with weights that vary by major.[13]

From the student's perspective, applying through the centralized system involves three main steps. First, students must complete high school with a GPA of at least 4.0 on a 1–7 scale.[14] Second, they must take the national college entrance exam (PSU),[15] which is administered annually in mid- to late December.[16] Third, applicants submit an ordered list of up to ten preferred college–major combinations. To support families in this process, the organization overseeing centralized admissions (DEMRE) maintains an official website with comprehensive information on procedures, timelines, and participating institutions.[17]

Applicants to the centralized system are matched to programs using a deferred acceptance (DA) algorithm.[18] A key theoretical property of the DA mechanism is that it

[13]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.

[14]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.

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

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

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

[18]In each round, students apply to their highest-ranked available program, which tentatively accepts

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 A2 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.

2.3. The Relative Ranking Policy

In June 2012, to support students from low-ranked high schools with strong grades but lower PSU scores, the Consejo de Rectores de Chile (CRUCH) introduced a new component to the college admission criteria: the *Relative Ranking* (RR) bonus. This measure compares a student's GPA with the average GPA of the three previous graduating cohorts from the same school. Because students are evaluated relative to earlier cohorts at their own school, they do not compete with peers from their same class for a higher RR score.

The standardized Relative Ranking (RR) score is derived from a nonlinear transformation of a student's high school GPA. When a student's GPA is below the average of the three previous cohorts at their school, their RR score equals their standardized GPA score (SGPA). When the GPA lies between that average and the highest GPA observed among those cohorts, the student receives a proportional bonus. Finally, students whose GPA exceeds the highest GPA of the prior three cohorts receive the maximum RR score of 850 points. Figure 2 illustrates this mapping: the blue line depicts the linear transformation from GPA to SGPA, while the red line shows the nonlinear relationship between GPA and the standardized RR score. In the figure, $\underline{r}_s$ denotes the average GPA across the three

applicants up to capacity based on their Admission Score (AS). Rejected students move to their next choice. The process repeats until no applicant can improve their assignment.

previous cohorts, and $\bar{r}_S$ the maximum GPA within those cohorts. I use the same notation throughout the paper.

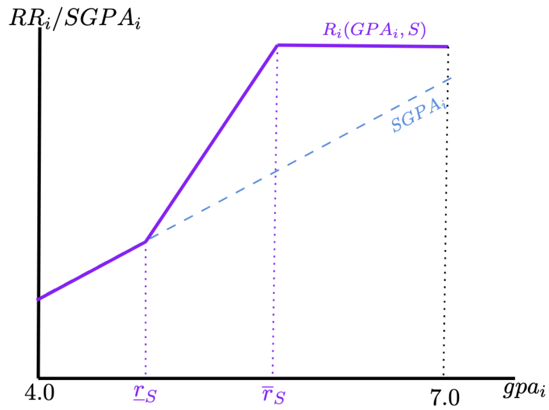


FIGURE 2. Relative Ranking Component Visualization

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. $\bar{r}_S$ represents the maximum threshold, which is equal to the best student from the three previous cohorts' GPA.

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,[19] 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, and that will be the case for the current academic year as well.

2.4. Tertiary Education

Table 1 summarizes key characteristics of post-secondary institutions for the 2014 academic year. Within the centralized system, public universities place greater weight on the RR component and less on the quantitative PSU section compared with private universities.

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

The average enrollment capacity per major is roughly 46 students across institution types, with larger cohorts in private institutions. Average annual tuition (in Chilean pesos) is similar for public and private universities within the centralized system but tends to be higher than at institutions outside it. Public and private universities also display comparable distributions of STEM programs and accreditation levels.

Although tuition and other institutional characteristics are broadly similar across university types, those participating in the centralized admission system are generally perceived as higher quality. According to the 2022 *Times Higher Education* (THE) Latin America ranking,[20] these institutions dominate the region's top positions, reinforcing their reputation as the most selective and prestigious in the country.

3. CONCEPTUAL FRAMEWORK

I develop a simple theoretical model to identify which students have incentives to game the policy by switching schools and to assess how such switching behavior may affect the policy's overall effectiveness. Because the policy compares students only within the school from which they graduate, there is no strategic advantage to moving earlier. I therefore focus on twelfth graders' decisions to switch schools.

In the first part of this section, I theoretically derive the main drivers of students' potential gains under the policy. I then present a model of school-switching decisions that incorporates the costs associated with switching. Finally, I analyze how the application cutoff and the composition of the admitted student body change across different scenarios.

3.1. Potential Gains in Students' Application Scores

Suppose there are two high schools, L and H, one college C, and a continuum of students of mass 1 applying to the college from both schools. A fraction μ_H of students attend school H, and the remaining $1 - \mu_H$ attend school L. Each high school is characterized by two predetermined parameters: the mean threshold $\underline{r}$ and the maximum threshold $\overline{r}$. All

[20] Source: https://www.timeshighereducation.com/student/best-universities/best-universities-latin-america. Pontificia Universidad Católica and Universidad de Chile ranked first and seventh, respectively, and all other Chilean universities in the top 50 also belong to the centralized admission system.

TABLE 1. Universities Characteristics by Allocation System and Type of Institution for Academic Year 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	37.91	46.47	43.75	43.83	47.98
Annual tuition (in CLP)	2,197,323.16	2,435,061.22	2,353,039.42	1,237,337.38	1,185,249.22
Ratio stem degree	0.31	0.38	0.04	0.00	0.00
Ratio accredited majors	0.37	0.40	0.32	0.24	0.21
Number of programs	849	545	2032	3185	1630
Panel 2: *Enrolled students*					
Total enrollment	39,383.00	29,549.00	76,432.00	126,551.00	65,429.00
Total female enrollment	19,208.00	13,829.00	42,053.00	62,420.00	32,972.00
Panel 3: *Application requirements' weights*					
average weight high school GPA	15.80	17.90	22.79	.	.
average weight relative ranking	26.05	22.60	16.90	.	.
average weight PSU verbal	20.69	18.07	38.12	.	.
average weight PSU quantitative	24.63	28.60	40.92	.	.

Note: This table reports colleges main characteristics by type of institution for academic year 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.

thresholds are publicly known when students make their relocation decisions in twelfth grade.

Consider now a setting in which students have already been assigned to a high school, and their only decision is whether to switch to another school. While the initial school choice decision is important and has been widely studied elsewhere (Alves et al. 2015; Pop-Eleches and Urquiola 2013; Hastings, Neilson, and Zimmerman 2012; Neilson 2013; Allende 2019), I take students' initial assignment as given and focus exclusively on the switching decision. The college C is characterized by its capacity constraint K and its preferences based on students' application scores. For the purposes of the model, I assume that students' scores depend only on their relative ranking.[21] Each student is characterized by a GPA $gpa_i \in (\underline{g}, \overline{g})$ and an initial high school $s \in \{L, H\}$.

Before the policy, student i's application score (AS_i) is a linear function of their GPA only:[22,23]

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

where θ is a constant term.

After the policy's introduction, the mapping from student i's GPA to application scores is determined by a nonlinear function of their GPA relative to the school from which they graduated—school e:

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

The parameters α_e and θ_e capture the slope and constants normalization factors specific

[21] This assumption holds if students' high school GPA and PSU scores are unaffected by the switching decision.

[22] This formula follows the official conversion table published by MINEDUC. See https://demre.cl/proceso-admision/factores-seleccion/tabla-transformacion-nem.

[23] Note that AS_i does not vary across schools in equation (1).

to school e respectively, while $\overline{AS}$ represents the upper bound of the standardized score.

This non-linear function implies: (i) a student gets the same application score as before the policy if they are not above $\underline{r}_e$, (ii) a student obtains a school-specific bonus if they are above $\underline{r}_e$ but below $\overline{r}_e$ in their school, and (iii) a student obtains the maximum possible score whenever their GPA is higher than $\overline{r}_e$.

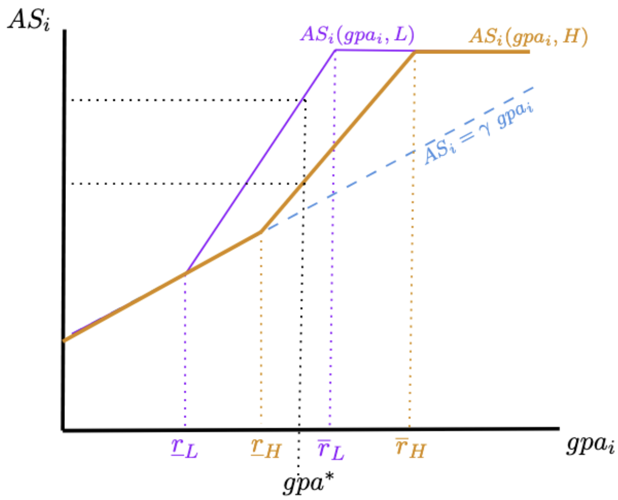


FIGURE 3. Same Thresholds' Order

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.

Figure 3 graphically illustrates the case in which school H has higher thresholds than school L.[24] In general terms, I assume that a student starting twelfth grade in school s has a potential gain in their application score from 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 3, students from school H have a potential gain in their application score by

[24] Although other combinations are possible, I do not discuss them in detail for two reasons. First, in Chile, schools with higher $\underline{r}$ tend to also have higher $\overline{r}$ (see Table A1). Second, I do not impose any restrictions in the empirical analysis when calculating students' potential gains.

switching to school L, but no student from school L is better off—in terms of application scores—by switching to school H, therefore $s = H$ and $e = L$.

3.2. A Simple Model of School Switching

The model developed in this section builds on the theoretical frameworks of Cullen, Long, and Reback (2013) and Estevan, Gall, and Morin (2019). I assume that all students apply to college,[25] and derive a utility U_{iC} if they are accepted. If they are not accepted, their utility is zero.

All students are ranked according to their application scores when applying to college. The allocation mechanism admits students with scores above a cutoff, where the cutoff is an equilibrium outcome.[26]

I assume that students pay a cost $c_{ise} > 0$ when switching from school s to school e, for all $e \in \{H, L\} \setminus \{s\}$. In addition, students derive school-specific utility, with $b_{is} > b_{ie}$.[27]

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

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

while their conditional utility from switching to school e is

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

Let $\Delta V_{i(s \to e)}$ denote the change in indirect utility from switching from school s to school e. Then, the change in utility from switching to any school e in the choice set can be defined

[25] Although this is a strong assumption, it is reasonable given that the policy directly affects application scores and thus the pool of students who already were interested in the college application process.

[26] If $K < 1$, only a fraction K of the total population (normalized to one) is accepted into college. Note that other students' decisions affect student i only through changes in the equilibrium cutoff.

[27] This assumption is consistent with the fact that families chose school s at the beginning of secondary education (grade 9).

as

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

As shown in equation (3), the only case in which a student gains utility from switching is when they are below the equilibrium cutoff if they remain in school s, but would exceed it if they graduated from school e. In that case,

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

Equation (4) shows that, relative to the overall cost of switching schools, $\tilde{c}_{ise}$, the value of college admission must be sufficiently large for a student to find it optimal to switch.

3.3. Application Scores and the Pool of Accepted Students in Equilibrium

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 that students' GPAs 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 fractions of students in each school before any switching occurs.[28] Given equations (1) and (2), I can define the distributions of application scores in each school as transformations of the GPA distributions. Let $G_L(AS)$ and $G_H(AS)$ denote the corresponding distributions for schools L and H, respectively. Under this setup, two equilibrium conditions characterize the application score cutoff and the pool of students

[28] Recall that $\mu_L + \mu_H = 1$.

accepted into college under any policy.

Constraint: Unique application score. Due to the centralized application system, and no quotas in the system, the application score in equilibrium is unique. Let gpa_L^* and gpa_H^* be the student's GPA that obtains an application score equal to the cutoff in equilibrium. Therefore:[29]

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

Constraint: College capacity. Let $d_H = 1$ if $AS_H(x) > AS_L(x)$ for the GPA level x. For any policy that does not affect the college capacity constraint, the share of students accepted in equilibrium must equal the share of available seats. Thus,

$$\begin{aligned} &\mu_L \cdot \underbrace{(1 - G_L(AS_L(gpa_L^*)))}_{AS > AS^* \text{ in } L} + \mu_L \cdot (1 - d_H) \cdot \underbrace{[G_L(AS_L(gpa_L^*)) - G_L(AS_L(gpa_H^*))]}_{\text{movers from } L \text{ to } H} \\ &+ \mu_H \cdot \underbrace{(1 - G_H(AS_H(gpa_H^*)))}_{AS > AS^* \text{ in } H} + \mu_H \cdot d_H \cdot \underbrace{[G_H(AS_H(gpa_H^*)) - G_H(AS_H(gpa_L^*))]}_{\text{movers from } H \text{ to } L} = \underbrace{K}_{\text{college capacity}}. \end{aligned} \tag{7}$$

3.3.1. 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 students accepted into college from each school, corresponding to those whose application scores exceed the equilibrium cutoff.
b. AS^* is the unique *competitive market* application cutoff given the number of available slots in college, subject to students' acceptance rates from schools L and H, q_L and q_H, which are also a function of the cutoff.

PROPOSITION 1. *Before policy implementation and using Equation* (1)*, students with* $gpa_i \geq$

[29] 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.

gpa_0^* are accepted into college from each school. Additionally, no student has an incentive to switch schools, and each school fills a fraction of the available seats equal to its share of the student population multiplied by the mass of students whose application scores exceed AS_0^*.

Recall that before the policy, the application score (AS) function was independent of students' schools and depended only on their GPA, which is assumed to be determined when they decide whether to switch schools. To build intuition for this proposition, consider Constraints 3.3 and 3.3. From Constraint 3.3, we have $AS_L(gpa_L^*) = AS_H(gpa_H^*) = AS^*$. Using the deterministic relationship between GPA and AS before the policy in Equation **??**, it follows that $gpa_L^* = gpa_H^*$. Finally, under the assumption that both GPA distributions are identical, Constraint 3.3 implies that, in the absence of switching, $G_L(AS^*) = G_H(AS^*) = G(AS^*)$. For the formal proof, see Appendix B.

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

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

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 college admission, denoted* gpa_H^* *and* gpa_L^**, respectively. As a consequence, the mass of accepted students increases in the school with the lower* gpa^* *and decreases in the other. Finally,* AS^* *rises relative to the outcome before the policy.*

For simplicity, assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L < \overline{r}_H$, as in Figure 3. Then, using Constraint 3.3 and the fact that Equation **??** always yields a weakly higher application score 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, applying the capacity constraint, we obtain:

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

Since $gpa_L^* < gpa_H^*$, and assuming once more equal GPA distributions, it follows that

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

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

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

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 college admission,* gpa_H^* *and* gpa_L^**. After the policy is implemented, the equilibrium application score increases. Finally, the impact of the policy, in terms of changes in the pool of admitted students, depends on how costly it is for students to switch schools.*

Proposition 3 follows a similar intuition to Proposition 2. The main difference is that now, due to switching, the application score increases further whenever the cost of switching, $\tilde{c}_{ijk}$, is strictly lower than the value of college (see proof in Appendix B). To see why the change in the pool of accepted students—one of the policy's goals—depends on the cost of switching, suppose that the cost is zero. Then, all students who have a potential gain from switching will move. In the case illustrated in Figure 3, 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 the policy on the number of students accepted into college from school L is reversed, and there is no change in the overall pool of accepted students.

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

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

3.4. Model's Main Predictions

The model generates insights about high school students' switching behavior and its implications for college admissions outcomes.

First, only students in the middle of the school-specific GPA distribution experience a positive change in their application score from switching schools. These differences in gains arise from the non-linear function used to compute application scores in my setting. Second, students in high-performing schools are more likely to have a positive score gain—this follows from the fact that high-performing schools have higher thresholds in the application score function. Finally, two conditions must hold for students with a positive gain to be willing to switch schools: (i) the increase in their application score must be large enough to change their admission outcome from rejection to acceptance, and (ii) they must value college more than the cost of switching, which includes both differences in school preferences and any direct switching costs.

4. DATA

4.1. Administrative Data Sources

This paper combines four administrative data sources from the Chilean education system, covering students enrolled in 12th grade nationwide between 2010 and 2018. The Ministry of Education (MINEDUC) provides 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 records from MINEDUC containing college–major information, including the weights assigned to each application score component, the number of available seats, and program-level details.

The second dataset comes from the agency in charge of the centralized college admission system (Departamento de Evaluación, Medición y Registro Educacional - DEMRE). These data include national test scores by subject, students' ranked lists of up to ten college–major preferences, and household characteristics at the student level.

The third set of administrative records is provided by the Education Quality Agency (Agencia de la Calidad de la Educación), including students' scores on the 10th-grade standardized test (SIMCE), self-reported socioeconomic status (SES), and parental education and aspirations.

Finally, from the publicly available data from the national regulatory agency (Consejo Nacional de Educacion - CNED), I obtain program information such as accreditation status, posted tuition and student body characteristics.

4.2. Data Limitations

Although Chilean administrative data offer rich student-level information, the data used in this paper have two main limitations. First, I do not directly observe students' socioeconomic status (SES). The available data include only self-reported income brackets for students applying to college, which are used to determine financial aid eligibility and are therefore likely underreported. To be able to characterize students by socioeconomic status, I rely on maternal education as a proxy. This measure has two advantages over self-reported income: it is not tied to financial aid decisions and is available for all students, regardless of whether they apply to college. While I cannot directly validate its correlation with income measures at the individual level, Figure A1 shows a strong association at the school level—the correlation between the share of students whose mothers did not complete high school and the school's vulnerability index is 0.79.

Second, I do not have access to students' home addresses, which limits my ability to define students' local school markets. I approximate residential locations using the geolocation of each student's primary school. Using this proxy, I construct buffers to define each student's relevant choice set.[30] Figure A2 shows the share of students living in the same county during primary and secondary school by year for Chile (panel A) and Santiago (panel B). In Chile, on average, 76.5% of students report living in the same county throughout their K–12 education, whereas in Santiago the corresponding share is approximately 74%. Both patterns are somehow stable across years.

4.3. Variables Construction and Descriptive Statistics

Using the census of schools and students from MINEDUC for cohorts entering twelfth grade between 2010 and 2018, I construct two variables that identify the treatment status and one of the main outcomes of interest. First, I create the treatment variable—the *positive potential gain* indicator—which measures whether a student could experience an increase in their college application score due to a higher RR score in alternative schools within their relevant school market. Second, I construct a dummy variable indicating whether a student switches schools during their twelfth-grade academic year, which constitutes one of the primary outcomes of interest.

Table 2 presents descriptive statistics for the sample of students used to study switching behavior among twelfth-grade students. About 4% of students switch schools in their senior year of high school. Nearly 45% of students live in Santiago, and 90% attend either

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

public (36%) or voucher (53%) high schools. Finally, 71% have a mother with at least a high school diploma, and a similar share of students nationwide report having access to the internet at home.

TABLE 2. Summary Statistics for Students in Twelfth Grade

	All		No positive gain		Positive gain	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
***Panel A:** Main dependent variables*						
Switch schools	0.04	0.21	0.05	0.22	0.03	0.17
Switch schools during the academic year	0.02	0.13	0.02	0.15	0.01	0.11
***Panel B:** Characteristics (Used as Controls in decile bins)*						
GPA (non-standardized)	5.55	0.50	5.37	0.44	5.88	0.43
10th grade standardized score	0.17	0.99	-0.11	0.92	0.62	0.93
***Panel C:** Characteristics (Not Used as Controls)*						
Other areas	0.57	0.49	0.58	0.49	0.55	0.50
Santiago	0.43	0.49	0.42	0.49	0.45	0.50
Attending public schools	0.36	0.48	0.39	0.49	0.31	0.46
Attending voucher schools	0.53	0.50	0.54	0.50	0.52	0.50
Attending pricate schools	0.11	0.31	0.07	0.26	0.17	0.38
Attending national test prep. track	0.51	0.50	0.41	0.49	0.69	0.46
Attending vocational track	0.35	0.48	0.41	0.49	0.25	0.43
Atending Q1 schools	0.16	0.36	0.20	0.40	0.09	0.28
Atending Q2 schools	0.24	0.42	0.27	0.45	0.17	0.38
Atending Q3 schools	0.26	0.44	0.26	0.44	0.25	0.43
Atending Q4 schools	0.35	0.48	0.27	0.44	0.49	0.50
Mother education < HS	0.29	0.45	0.33	0.47	0.22	0.41
Mother education = HS	0.45	0.50	0.46	0.50	0.44	0.50
Mother education > HS	0.26	0.44	0.21	0.41	0.34	0.47
Male	0.49	0.50	0.52	0.50	0.43	0.50
Female	0.51	0.50	0.48	0.50	0.57	0.50
Low aspirations	0.30	0.46	0.37	0.48	0.17	0.38
High aspirations	0.70	0.46	0.63	0.48	0.83	0.38
Does not have access to internet	0.24	0.43	0.28	0.45	0.20	0.40
Has access to internet	0.76	0.43	0.72	0.45	0.80	0.40
Observations	1,288,129		808,937		479,192	

Note: This table presents summary statistics for the twelfth-grade students in my sample from the Chilean Educational Census. Panel A reports the main dependent variables, switching schools and switching only during the academic year, while panel B includes control variables used in main analysis. Scores are controlled via deciles group fixed effects. Panel C provides additional characteristics that I explore as heterogeneities in the main analysis (not used as controls). The sample is split by students with and without positive gain in their relevant educational markets, which is defined as a 2 km radius buffer around students' primary schools. The cohorts of senior students used in the study range from 2010 to 2018.

For students' college-related outcomes—such as application, admission, enrollment, dropout, and on-time graduation—I use administrative records from the agency in charge of the centralized college admission system (DEMRE). I restrict the analysis to cohorts graduating from high school between 2011 and 2016 for two reasons. First, beginning with the 2012 admission cycle—which, for the purposes of this analysis, corresponds to students graduating in 2011 or later, since I focus on applicants who enroll in college the year after graduation—eight additional universities joined the centralized admission system. This change increases the number of on-platform slots by approximately 40% (see Kapor, Karnani, and Neilson (2024)). Second, because college completion in Chile takes substantial time—on average six years, with nearly 9 out of 10 students taking up to seven years—the availability of graduation outcomes declines sharply for more recent cohorts, limiting the analysis of post-enrollment outcomes for younger students.

Table 3 presents the main summary statistics for the sample of students applying to college using the centralized system, where 33 universities participate. 25% of the students applying applied at least to one elite university (PUC and UCH) within their three most preferred majors. Among all the applicants, almost 80% are accepted to one of the majors they ranked. When considering acceptance and enrollment rates, 10% of the applicants are accepted into an elite university, and a similar share enrolled in that type of institution. Now, when considering university graduation, 23% of applicants graduate from a university on time.

In terms of student characteristics, applicants to universities participating in the centralized admission system–who represent about 51% of all high school graduates–exhibit stronger academic performance than the overall population of graduates. This selection into college application is expected, given the high selectivity of the centralized admission system. Applicants are also disproportionately drawn from private schools and high-performing high schools (quartalies Q3 and Q4), which account for roughly 20% and 80% of the applicant pool, respectively.

Finally, for high school performance, I use SIMCE data to classify schools in quality quartiles, based on the average scores from the national standardized test taken by tenth-grade students in 2010. Although I can observe cohorts of students taking the 10th grade standardized test in years 2010, 2012, 2014-2018. Table A1 presents the main characteristics of each type of school.

TABLE 3. Summary Statistics for Students Applying to Universities in the Centralized System

	All		No positive gain		Positive gain	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
***Panel A:** Main dependent variables*						
Applied to at least an elite university within their 3 most preferred majors	0.25	0.43	0.16	0.36	0.33	0.47
Accepted in a university	0.79	0.41	0.70	0.46	0.86	0.35
Accepted in an elite university	0.10	0.30	0.05	0.22	0.14	0.35
Enrolled in a university	0.71	0.45	0.63	0.48	0.78	0.41
Enrolled in an elite university	0.10	0.30	0.05	0.22	0.14	0.34
Graduated on time	0.29	0.46	0.23	0.42	0.35	0.48
Graduated at all	0.23	0.42	0.18	0.38	0.28	0.45
***Panel B:** Characteristics (Used as Controls in decile bins)*						
GPA (non-standardized)	5.85	0.47	5.64	0.48	6.03	0.38
10th grade standardized score	0.77	0.81	0.51	0.82	0.98	0.74
***Panel C:** Characteristics (Not Used as Controls)*						
Other areas	0.59	0.49	0.62	0.48	0.56	0.50
Santiago	0.41	0.49	0.38	0.48	0.44	0.50
Attending public schools	0.23	0.42	0.24	0.43	0.23	0.42
Attending voucher schools	0.55	0.50	0.59	0.49	0.52	0.50
Attending pricate schools	0.22	0.41	0.18	0.38	0.25	0.43
Attending national test prep. track	0.81	0.39	0.74	0.44	0.87	0.34
Attending vocational track	0.15	0.36	0.20	0.40	0.11	0.31
Atending Q1 schools	0.06	0.24	0.10	0.30	0.03	0.18
Atending Q2 schools	0.16	0.37	0.21	0.40	0.12	0.33
Atending Q3 schools	0.26	0.44	0.28	0.45	0.24	0.43
Atending Q4 schools	0.52	0.50	0.42	0.49	0.60	0.49
Mother education < HS	0.16	0.37	0.19	0.39	0.14	0.35
Mother education = HS	0.45	0.50	0.47	0.50	0.44	0.50
Mother education > HS	0.39	0.49	0.34	0.47	0.42	0.49
Male	0.46	0.50	0.49	0.50	0.44	0.50
Female	0.54	0.50	0.51	0.50	0.56	0.50
Low aspirations	0.09	0.29	0.13	0.34	0.06	0.23
High aspirations	0.91	0.29	0.87	0.34	0.94	0.23
Does not have access to internet	0.14	0.35	0.16	0.37	0.13	0.33
Has access to internet	0.86	0.35	0.84	0.37	0.87	0.33
Share of students graduating from twelfth grade	0.51	0.50	0.40	0.49	0.69	0.46
Observations	369,579		168,138		201,441	

Note: This table presents summary statistics for the applicants to universities who applied to college to start tertiary education the year after graduation in my sample from DEMRE. Panel A reports the main dependent variables, applying, being admitted, enrolling, and graduating from college, while panel B includes control variables used in main analysis. Scores are controlled via deciles group fixed effects. Panel C provides additional characteristics that I explore as heterogeneities in the main analysis (not used as controls). The sample is split by students with and without positive gain in their relevant educational markets, which is defined as a 2 km radius buffer around students' primary schools. The cohorts of senior students used in the study range from 2011 to 2016.

I. **Potential Gain**

A student's *potential gain* (PG) is the difference between the relative ranking score they would obtain if they had 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 initial school s. The *median potential gain* (MPG) corresponds to the median of these gains across all schools in the student's relevant school market. Each student's relevant market is constructed as the set of high schools located within a 2 km radius of their primary school (see Section 4.2 for data limitations and Appendix A for details on how relevant markets, or choice sets, are calculated).

To compute these measures, I calculate the counterfactual application score each student would obtain if they had graduated from each alternative school in their choice set and compare these scores to the one associated with their actual school. Although students' actual ranking scores are reported in the DEMRE data, I also simulate these using the same procedure to maintain internal consistency and to avoid introducing non-random measurement error. Because the formula relies exclusively on pre-determined variables (see Section 2.3 for details), I can calculate MPG for any cohort, including those that applied before the policy was implemented.

For this exercise to be informative about students switching schools as a result of the incentives created by the RR policy, two conditions must hold. First, families should not sort residentially into different school markets in response to the policy. Second, any measurement error in the *potential gain* variable should be classical—that is, uncorrelated with students' switching behavior or admission outcomes.

To mitigate these concerns, I rely on features of the Chilean educational context. First, in Chile, students are not assigned to schools based on residence, which limits incentives for selective migration following policy changes. Consistently, around 77% of students remain in the same county where they attended primary school during the period of analysis. Second, following a similar strategy than Chetty et al. (2014), I construct each student's relevant market using the location of their primary school rather than their high school at the start of grade 12. This approach ensures that the construction of the treatment variable is exogenous to students' subsequent switching or migration decisions. Finally, in Appendix E I re-estimate my main analysis restricting the sample to students living in the same county–the results are robust to this exercise.

To validate the accuracy of the constructed relative ranking score, I replicate the official score using my formula for cohorts graduating from 2012 onward and compare it against the one reported in administrative records.[31] Figure A3 presents the distribution of these differences. Across the years displayed, the mean difference between the two measures is 0.43 points.

Using each student's *median potential gain*, I classify students into two groups: those with a positive gain from switching schools ($MPG > 0$) and those without ($MPG \leq 0$). Students with a positive gain are considered part of the treated group ($positive\_gain = 1$), while those with no gain conform the control group ($positive\_gain = 0$). On average, 35% of twelfth-grade students nationwide have a positive median gain within their relevant market. Among students residing in the Metropolitan Region (Santiago), the share is slightly higher, at 36%.

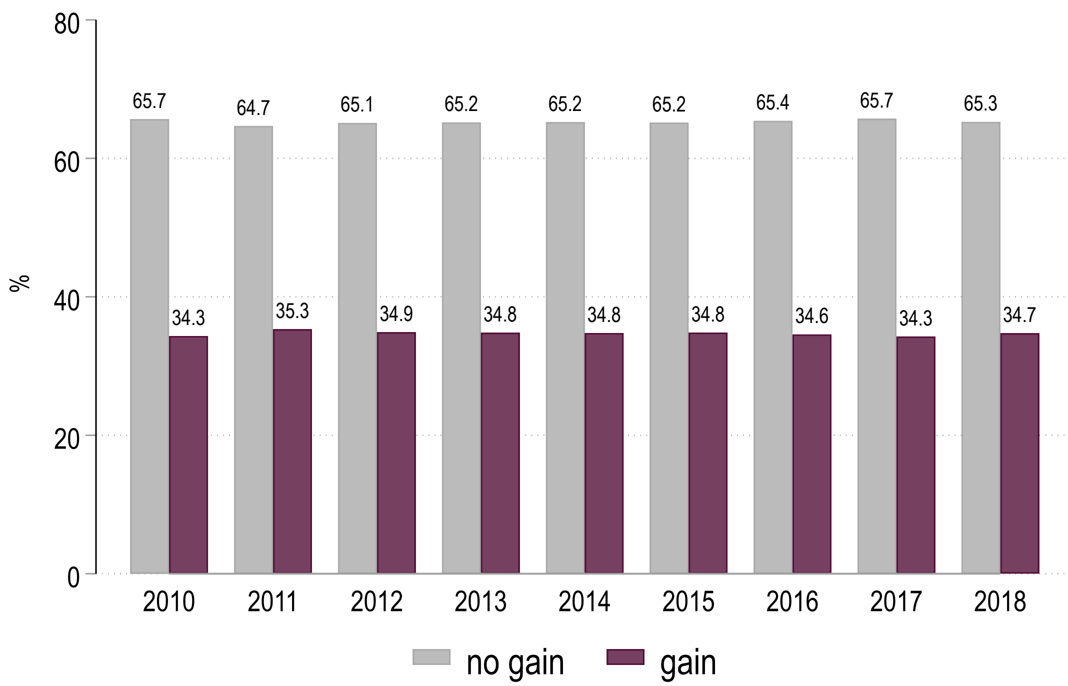


FIGURE 4. Ratio Students with Positive Potential Gain.

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 4 plots the share of students with positive gain by year, and Figure A4 compares

[31]This validation cannot be performed for cohorts before 2012, since the relative ranking score did not exist prior to that year.

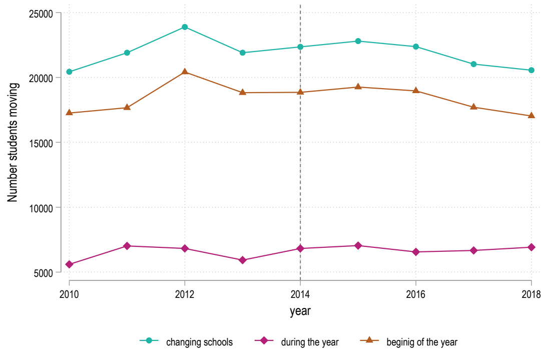
the distribution of median potential gains for students in the Metropolitan Region relative to those in other regions over time. Overall, there are no systematic differences across cohorts in the proportion of students with a positive gain or in the distribution of median potential gains across regions. The absence of differences between cohorts exposed and not exposed to the policy provides reassuring evidence that the *positive potential gain* variable serves as a valid and stable instrument to estimate the effect of the policy in strategic relocation during twelfth grade. Finally, in Tables 2 and 3 Columns 4-7, I present the main descriptive statistics for my sample of high school graduates and applicants to college separately for students with no gain (Columns 4 and 5) and with gain (Columns 6 and 7).

II. **Switching Schools during Twelfth Grade**

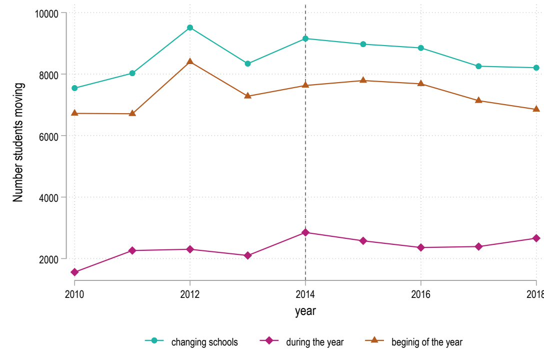
I focus on students' switching decisions in twelfth grade because the policy implementation created incentives to relocate at the last possible moment (see Section 2.3). The Chilean context provides two institutional features that allow me to distinguish transfers occurring at the beginning of the academic year from those occurring during it.[32] First, enrollment is recorded in March (the start of the academic year) and again in December (when grades are published). Second, students are permitted to transfer schools at any time during the year, provided that parents request the transfer and the original school completes a form reporting the student's GPA up to that point.

Figure 5 presents the number of students switching schools in twelfth grade between 2010 and 2018, distinguishing between those who switch at the beginning of the year and those who switch mid-year, for the entire country (Panel A), Santiago (Panel B), high-performing schools nationwide (Panel C), and high-performing schools in Santiago (Panel D). On average, around 21,000 students transfer schools during their final year, with roughly one in three doing so during the academic year rather than before it starts. Students in Santiago account for about one-third of all transfers nationwide, displaying a similar temporal pattern to the national trend. Among high-performing schools (Panels C and D),

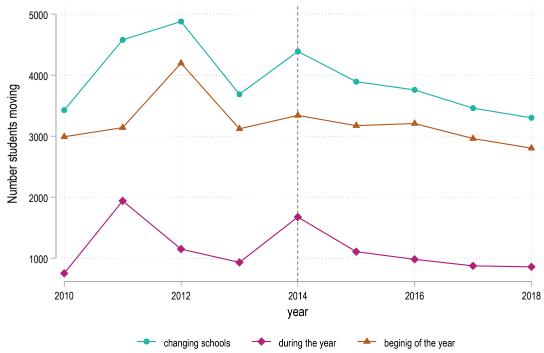
[32] I classify a student as switching at the beginning of the year if they appear enrolled in one school at the end of eleventh grade but are registered in a different school at the beginning of twelfth grade.



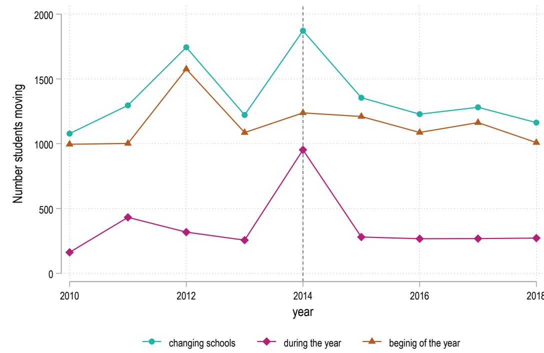
A. *All* students



B. Santiago



C. *High-Performing* Schools



D. *High-Performing* Schools in Santiago

FIGURE 5. Number of Students Switching Schools in Twelfth Grade (2010-2018)

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).

the total number of transfers is smaller but shows a distinct pattern: mid-year transfers peak in 2014, coinciding with the timing of the policy's disclosure. This suggests that students from higher-performing schools were more likely to respond strategically to the new incentives, as predicted by the model (see Section 3.4).

Although trends are relatively stable over time, there are two moments when mobility spikes noticeably. The first occurs following the massive student protests of mid-2011, which led to an influx of students switching schools at the beginning of 2012. The second spike occurs in 2014, the year the RR policy formula was made public. Importantly, the timing of these two episodes differs: as shown in Figure 5, the post-protest relocations in 2012 happened mostly at the start of the school year, whereas the 2014 increase was driven by mid-year transfers—consistent with a strategic response to the policy change. Overall, these patterns suggest that the policy did not generate a sharp rise in aggregate mobility but instead altered the timing and composition of transfers within preexisting dynamics of school switching.

5. EMPIRICAL SPECIFICATION

This section outlines the identification strategies used in this paper. The first strategy (5.1 and 5.2), a difference-in-differences (DD) event-study design, identifies the causal effect of the RR policy disclosure on students' strategic behavior and college admission outcomes among twelfth-grade students with and without high potential gains. The second strategy (**??**), a simulation analysis, estimates the distributional effects of the policy on the share of students accepted into college for the pool of students who graduated from high school in 2014. This second strategy compares acceptance rate for each students in (i) a market where no one is allowed to move, (ii) students who I observe switching schools did so, and (iii) every student with incentives did switch schools.

5.1. Switching Schools during Twelfth Grade

To examine the impact of the RR policy disclosure on students' strategic behavior during twelfth grade, I estimate the following specification:

$$switch_{istm} = postive\_gain_{ism} \cdot \sum_{\substack{\tau=2010 \\ \tau\neq 2013}}^{2018} \beta_\tau \mathbb{1}\{t=\tau\} + \delta_t + \delta_s + \delta_{gpa\_decile} + \varepsilon_{istm}, \tag{9}$$

where $switch_{istm}$ equals 1 if student i, attending school s at the beginning of grade 12 in year t and belonging to school market m, switched schools during that year, and 0 otherwise. The variable $positive\_gain_{ism}$ is a dummy equal to 1 if the student has a median positive gain from switching schools in their relative ranking score.

The binary treatment variable is interacted with event-year dummies, $\mathbb{1}\{t=\tau\}$, to test whether the policy disclosure affected students' behavior only in the year it was made public (i.e., 2014). The omitted category corresponds to the cohort in twelfth grade during

2013, the year immediately before the disclosure. Thus, each coefficient β_τ measures the difference in the probability of switching schools between students with positive median potential gains and those without, for a given cohort of twelfth graders, relative to the 2013 cohort.

I control for several sets of fixed effects. δ_t denotes twelfth-grade cohort dummies, which capture year-specific shocks that could affect any student's likelihood of switching schools. δ_s represents beginning-of-grade-12 school fixed effects, accounting for time-invariant differences across schools—such as disciplinary structure or administrative rigidity—that may influence switching behavior. Finally, δ_{gpa_decile} includes dummies for each decile in the within-school GPA distribution at the start of grade 12, controlling for time-invariant heterogeneity in students' incentives to switch schools across different points of the GPA distribution.

To interpret the estimated coefficients as causal effects, two identifying assumptions must hold. First, there should be no differential pre-trends in the outcome variable between students with high and low potential gains prior to the policy disclosure. Second, the treatment assignment—having a positive potential gain—must remain stable over time; that is, the likelihood of being classified as a high-gain student should not change for reasons unrelated to the policy. When these assumptions are satisfied, Equation 9 identifies the causal effect of the policy disclosure on students' strategic decision to switch schools.

5.2. University Application, Admission, and Enrollment

I also test the impact of the policy release on college admission outcomes using the same specification that for switching decision, but considering college outcomes. The specification I employ is:

$$(10)\quad college\_in\_outcome_{istm} = positive\_gain_{ism} \cdot \sum_{\substack{\tau=2010 \\ \tau\neq 2013}}^{2018} \beta_\tau \mathbb{1}\{t=\tau\} + \delta_t + \delta_s + \delta_{gpa\_decile} + \varepsilon_{istm},$$

As before, in this specification, the event of interest is the policy disclosure affecting students' behavior only in the year it was made public (i.e., 2014). The dependent variable $college\_in\_outcome_{istm}$ represents outcomes of interest for student i, starting twelfth grade in school s, belonging to the school market m in period t. Here the outcomes of interest are: (i) whether students apply, is accepted or enrolled in a university, (ii) apply, is accepted or enrolled in an elite university, or (iii) apply, is accepted or enrolled in a stem/traditional/high return/highly selective program.

The binary variable is again interacted with the event-year dummies, $\mathbb{1}\{t = \tau\}$, to investigate the effect of the policy disclosure. I use the same set of pre-determined controls as in analysis following equation 9. δ_s represents beginning-of-grade-12 school fixed effects, accounting for time-invariant differences across schools—such as disciplinary structure or administrative rigidity—that may influence switching behavior. Finally, δ_{gpa_decile} includes dummies for each decile in the within-school GPA distribution at the start of grade 12.

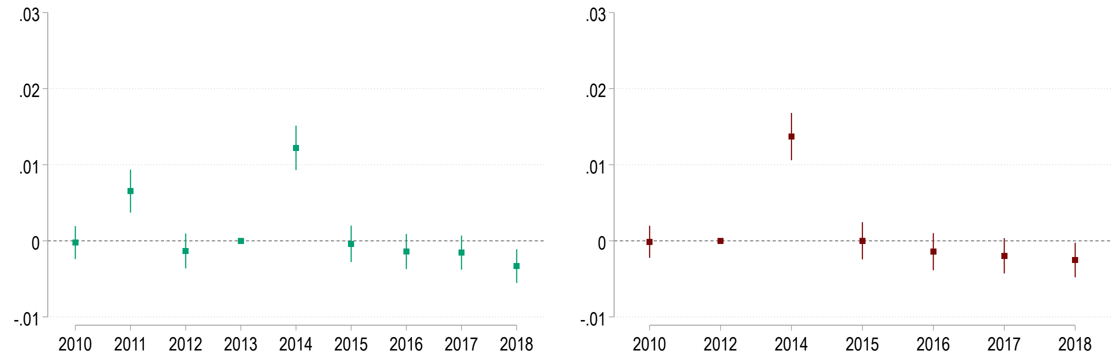
6. RESULTS

6.1. Switching Schools during Twelfth Grade

I begin the analysis by estimating the impact of the RR policy disclosure—the event of interest—on students' decisions to switch schools, using equation (9). The results show that the release of information significantly increased the likelihood that students switched schools during twelfth grade.

Figures 6 and 7 display the estimated coefficients on the interaction between the indicator for having a positive potential gain and the event-year dummies. Figure 6 presents results for the full national sample of twelfth-grade students, while Figure 7 shows results from separate estimations for Santiago and for the rest of the country. Appendix E reports analogous results using a restricted sample of students who, in twelfth grade, lived in the same county as during primary school.

Consistent with strategic behavior, students with a positive gain in their educational market are 1.2 percentage points more likely to switch schools during twelfth grade (p-value = 0.00) relative to the year before the RR policy formula was made public. This effect



A. Within-School GPA Controls

B. Standardized Test Controls

FIGURE 6. Impact of the RR Policy Disclosure on Students' Switching Schools during Twelfth Grade

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive potential gain and event-year dummies. Panel A includes fixed effects for within-school GPA deciles, while Panel B includes fixed effects for tenth-grade standardized test deciles. The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

represents an increase of 54% relative to the sample mean (0.019) in the pre-policy period (2010–2013). The coefficients for the years preceding the policy release are close to zero and statistically insignificant, except for 2011. As discussed in Section 2, 2011 coincides with the nationwide student protests that kept many schools closed for several months and led some students to change schools for non-policy-related reasons, as the RR policy was not yet under discussion. After 2014, the estimated difference in the likelihood of switching schools disappears, consistent with the subsequent policy change under which students were compared not only within the school from which they graduated but across all schools they attended (see Section 2.3 for details).

When separating the sample between Santiago and the rest of the country, three patterns emerge. First, the overall effect described above is entirely driven by students residing in Santiago. Among these students, having a positive gain in their educational market increases the likelihood of switching schools during twelfth grade by 2.4 percentage points (p-value = 0.00) relative to the year before the RR policy formula was made public, corresponding to a 140% increase relative to the 2010–2013 mean (0.017). A formal test of

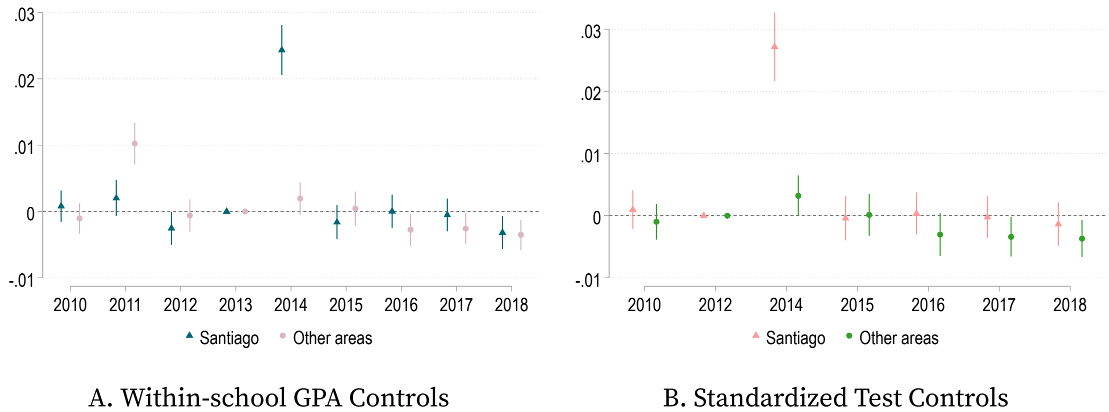


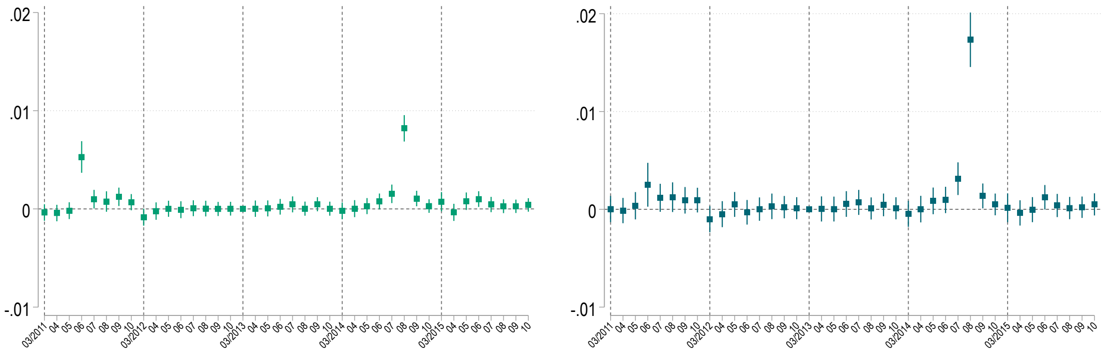
FIGURE 7. Impact of the RR Policy Disclosure on Students' Switching Schools during Twelfth Grade by Country's Areas

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive gain and event-year dummies, estimated separately for two samples: students living in Santiago (blue triangles) and students living in other areas (pink dots) . Panel A includes fixed effects for within-school GPA deciles, while Panel B includes fixed effects for tenth-grade standardized test deciles. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year, residing either in Santiago (triangles) or in other regions of the country (circles). The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

heterogeneous effects confirms that impacts differs significantly across the two samples ($F = 94.09$), indicating that the policy impact was statistically different between Santiago and other regions.

Second, for students in Santiago, the coefficients for the years preceding the policy release are close to zero and statistically insignificant, including 2011. Finally, consistent with strategic behavior, and as in Figure 6, after the 2015 policy change—when students began to be compared across all schools they attended rather than only the one from which they graduated—students with positive gains in their educational market were no longer more likely to switch schools than those without positive gains.

Overall, the results suggest that students reacted strategically by switching schools during the academic year following the public release of the RR formula. Figure 8 provides additional evidence using monthly attendance data from 2011 to 2015 to estimate Equation (9) on a month-by-month basis rather than yearly. The figure shows that students with a positive potential gain are more likely to switch schools toward the end of the academic year, providing further support for the interpretation that these transfers reflect strategic behavior.



A. Chile B. Santiago

FIGURE 8. Impact of the RR Policy Disclosure on Students' Switching Schools Month by Month during Twelfth Grade

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive gain and event-month dummies. Both estimations includes fixed effects for within-school GPA deciles. Panel A presents the results for the entire country, while Panel B uses only students living in Santiago. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year. The vertical dashed lines separate different academic years. The y-axis reports the change in the probability of switching relative to March 2013 (the omitted month). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

I also perform the same analysis focusing on school relocations that occur at the beginning of the academic year, with results presented in Figure A5. If students with a positive potential gain were not responding strategically to the policy's disclosure, we would expect to observe an increase in switching even at the start of the year. However, I find no significant change in the likelihood of switching schools at the beginning of the academic year for students with positive gains, supporting the interpretation that these transfers were driven by strategic considerations linked to the policy.

I. **Heterogeneities in Responses to the Policy Release**

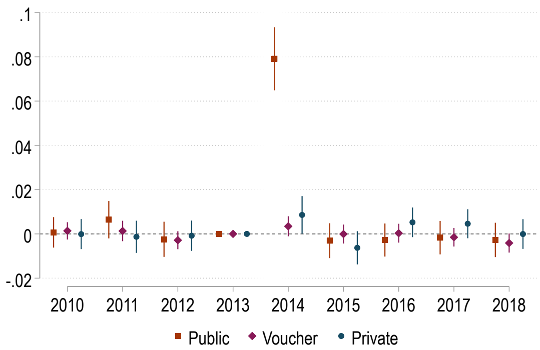
After estimating the average effect of the RR policy disclosure on school switching—and showing that it is entirely driven by students in Santiago—I investigate whether this response differs across groups of students and schools within the metropolitan area. Exploring heterogeneity in treatment effects helps uncover the mechanisms through which the policy shaped behavior and identifies which groups of students were most responsive to the incentives created by the policy information release. In particular, and as suggested by the model, I examine whether the impact varies by school performance. I also explore differences by parents' aspirations, students' socioeconomic background, school track, and school type (public, voucher, or private) to assess whether students faced different costs when deciding to switch schools. The results indicate that the ability to react strategically to new information was not evenly distributed across the population but was concentrated among high-SES students attending high-performing public schools whose parents had high educational aspirations for them even before the policy change.

Figures 9 and 10 plot the interaction coefficients between having a positive potential gain and event-year dummies, estimated using Equation 9, in samples divided according to different dimensions of heterogeneity. Figure 9, Panel A, examines differences across school types, Panel B focuses on heterogeneity by school performance, and Panel C explores variation by school track.

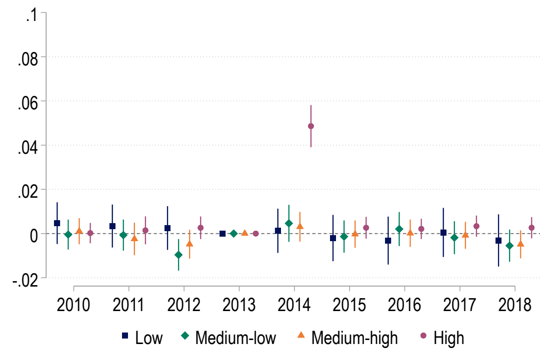
After the RR policy formula was made public, students attending public schools with a positive gain in their educational market increased their likelihood of switching schools during twelfth grade by 8 percentage points relative to the year before the disclosure. This effect represents a 300% increase compared to the 2010–2013 mean (0.025). In contrast, while the coefficients for students attending voucher and private schools are also positive, they are small in magnitude and not statistically significant at the 1% level.

Similarly, after the RR policy formula was made public, students attending high-performing schools with a positive gain increased their likelihood of switching schools during twelfth grade by 4.5 percentage points relative to the year before the disclosure. In contrast, there is no evidence that students attending lower-performing schools changed their behavior. This result is consistent with the model's predictions and the positive correlation between school thresholds and academic performance.

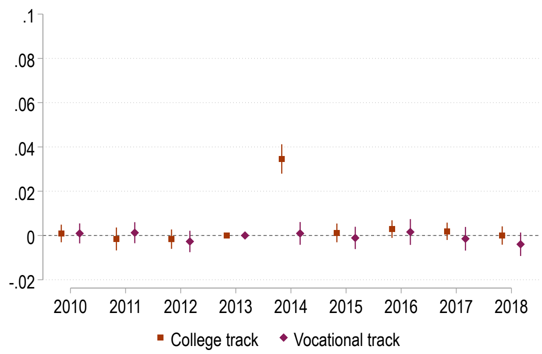
I also test whether students enrolled in different academic tracks reacted differently to the policy. In this case, one would expect that students following the college-preparatory track were the ones responding to the policy incentives. The heterogeneity analysis sup-



A. Type of School



B. School Performance



C. School Track

FIGURE 9. Heterogeneous Impact of the RR Policy Disclosure on Students' Switching Schools by School Characteristics

Note: This figure plots the coefficients from estimating equation (9) inhe rest the sample of students living in Santiago, where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive gain and event-year dummies, estimated separately for each sample. Panel A presents the results by type of school (public, voucher, or private). Panel B presents the results. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year. All the regressions include GPA deciles fixed effects. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

ports this hypothesis, showing that the rise in school switching occurred only among students in the college-preparatory track after the policy release.

To further explore the mechanisms driving students' responses to the RR policy disclosure, I examine heterogeneity in switching behavior across students characteristics. Figure 10 presents the coefficients from Equation 9, estimated separately by socioeconomic status (Panel A), parents' aspirations (Panel B), gender (Panel C), and internet access at home (Panel D). Because information on student-level characteristics is not available for 2011 and 2013, these years are excluded from the estimation.

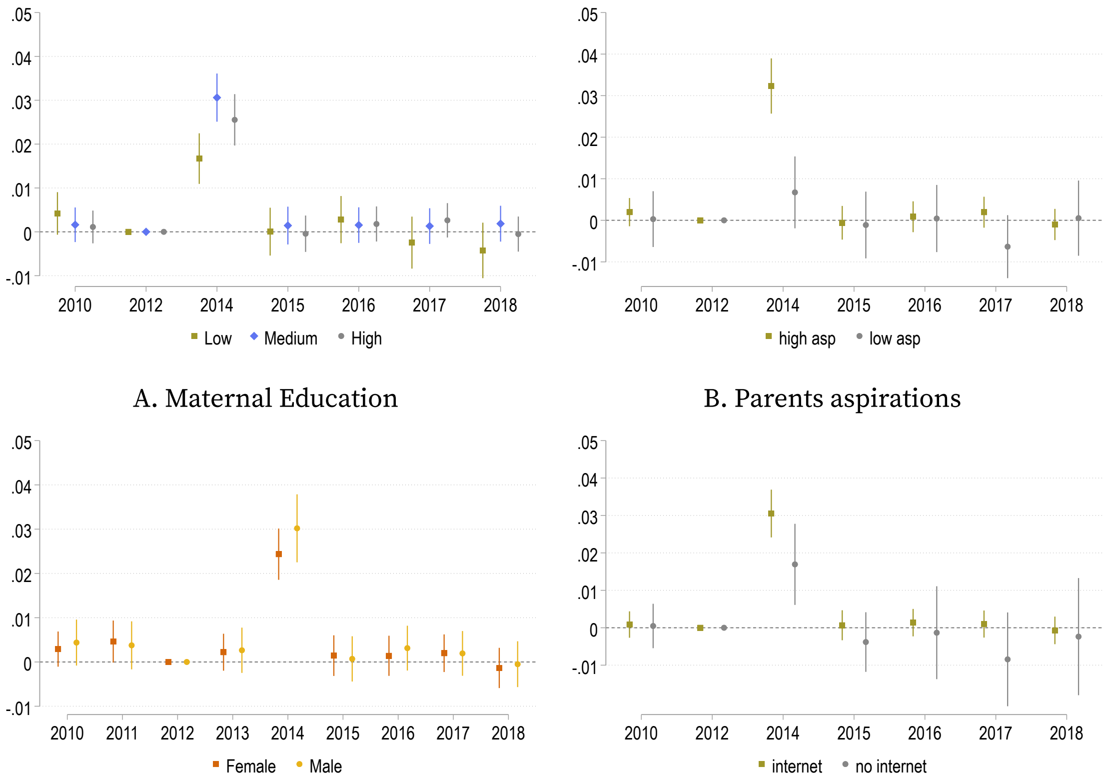
Panel A shows that students across all socioeconomic groups increased their likelihood of switching schools in 2014 relative to 2013, although the magnitude of the effect varies by SES level. The increase is smallest among low-SES students, while medium- and high-SES students exhibit similar and larger responses. To formally test whether the increase in switching behavior among higher-SES students differs from that of low-SES students, I conduct an interaction test between the 2014 event-year dummy and the SES variable, using low-SES as the reference group. The results indicate that only the difference between medium- and low-SES students is statistically significant at the 10% level (p-value = 0.06).

Panel B explores heterogeneity by parents' educational aspirations. The results show that only students whose parents held high educational aspirations responded to the policy by increasing their likelihood of switching schools by 3.2 percentage points relative to 2013. A formal test confirms that the difference between students with high-aspiration parents and others is statistically significant at the 1% level (p-value = 0.000). This finding indicates that parental expectations played a key role in shaping students' responsiveness to the policy information release, likely by influencing both the perceived returns to strategic behavior and the motivation to change academic environments at the end of high school.

Panels C and D examine heterogeneity by gender and internet access, respectively. Gender differences are small and statistically insignificant, suggesting that both male and female students responded similarly to the policy information release. Likewise, students with internet access at home were not significantly more likely to switch schools in 2014 compared to peers without access, although the difference in point estimates is larger than in the gender comparison and statistically different from each other only at the 5% significance level (p-value = 0.04).

II. **Additional Supporting Evidence of Strategic Behavior**

I next examine the characteristics of the schools to which students moved. To do so, I estimate Equation (9) using alternative outcomes that capture features of the destination (or "ending") schools. The results show that students targeted specific types of institutions rather than switching randomly. In particular, students tended to move to schools with



A. Maternal Education

B. Parents aspirations

C. Gender

D. Internet Access

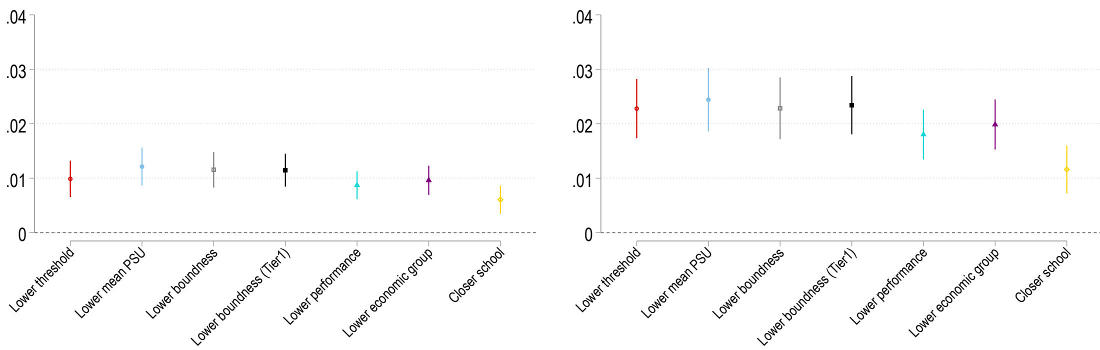
FIGURE 10. Heterogeneous Impact of the RR Policy Disclosure on Students' Switching Schools by Students Characteristics

Note: This figure plots the coefficients from estimating equation (9) in the sample of students living in Santiago, where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive gain and event-year dummies, estimated separately for each sample. Panel A presents the results by type of school (public, voucher, or private), Panel B presents the results by parents' educational aspirations, Panel C by gender, and Panel D by internet access at home. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year. All the regressions include GPA deciles fixed effects. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

lower RR formula thresholds[33]—as predicted by the theoretical framework—as well as to schools with a poorer socioeconomic composition, closer proximity to their home, lower college enrollment rates, and weaker academic performance. Figure 11 reports the point estimates and 99% confidence intervals for these outcomes, where each point estimate corresponds to the interaction coefficient between having a positive potential gain and the

[33]Recall that thresholds correspond to the average GPA and performance of the best students among the cohort that graduated from each school in the previous year.

2014-year dummy—the coefficient of interest—for Chile (left) and Santiago (right). Figures A7-A13 display the corresponding event-study estimates for each outcome separately.



A. Chile B. Santiago

FIGURE 11. Impact of the RR Policy Disclosure on Students' School Switching: Outcomes Related to Destination School Characteristics

Note: This figure plots the coefficients from estimating Equation (9) using outcomes related to destination school characteristics. Each point estimate represents the interaction coefficient between having a positive potential gain and the 2014-year dummy in a regression where the dependent variable is an indicator for switching schools in twelfth grade to a school with the characteristic shown on the x-axis. The coefficients are estimated separately for each outcome. Panel A reports the results for the entire country, while Panel B focuses on Santiago. Each sample includes cohorts of students entering twelfth grade in each year. All regressions include GPA decile fixed effects. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are displayed.

In the national sample (Panel A), students with a positive potential gain are about 1 percentage point more likely to transfer to schools with worse academic outcomes, to attend schools with more students from low-income backgrounds, and to be closer to home. These results are consistent with the theoretical framework: students appear to have moved to schools where they could improve their relative position and thus increase their admission chances. However, the estimated magnitudes are small, suggesting that, at the national level, these responses were not widespread.

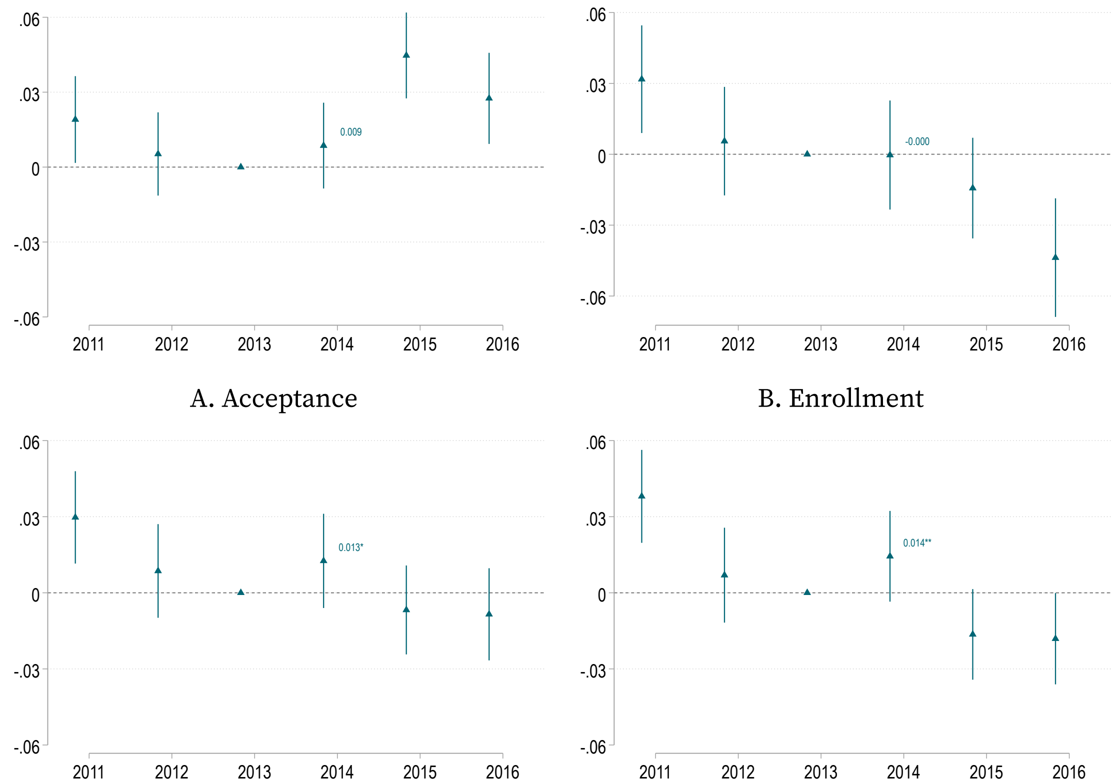
The results for Santiago (Panel B) are larger in magnitude, although less precisely estimated, given the smaller sample. Students with a positive potential gain are around 2.5 percentage points more likely to switch to schools with lower RR thresholds and lower post-graduation academic performance. They are also more likely to move to schools with a higher share of low-SES students and to schools located closer to their homes, although these effects are smaller. Overall the findings reinforce the previous evidence that most of the response to the RR policy formula disclosure was concentrated in Santiago, where students face more competitive and diverse educational markets.

6.2. Admission, Enrollment, and Completion in Post-Secondary Education

In this section, I estimate the impact of the RR policy disclosure on students' postsecondary outcomes using Equation (10). Focusing on students living in Santiago, the results show that having a positive potential gain does not increase overall admission to or enrollment in universities participating in the centralized admission system. Instead, students with positive gains become more likely to enroll in highly selective programs. At the same time, these students are less likely to graduate on time, suggesting that strategic school switching increased access to more selective programs but came at the cost of slower academic progression.

Figure 12 plots the coefficients on the interaction between the positive potential gain indicator and event-year dummies for students living in Santiago. Panel A reports results for overall admission, Panel B for enrollment, and Panels C and D examine admission to and enrollment in highly selective programs, respectively. I find that students with a positive potential gain are 1.3 p.p. more likely to be admitted to a highly selective program (p-value=0.081) and 1.4 p.p. more likely to enroll in such a program (p-value=0.038) in 2014, the year following the public release of the RR policy formula. Figure A14 shows that these effects are not driven by admission to or enrollment in elite universities (Panel A), traditional programs (Panel B), STEM programs (Panel C), or high-return programs (Panel D).

Next, I examine whether the results are consistent with the mismatch hypothesis. To do so, I estimate Equation (9) using dropout, graduation, and on-time graduation as outcomes. An increase in dropout rates or a decline in graduation rates following the RR policy release would indicate that students who had a positive gain by switching high schools were admitted to programs for which they were less well prepared. Figure 13 presents the corresponding difference-in-differences event-study estimates. I find no effects on students' likelihood of dropping out or on overall graduation rates. However,



A. Acceptance

B. Enrollment

C. Acceptance in High Selective Programs

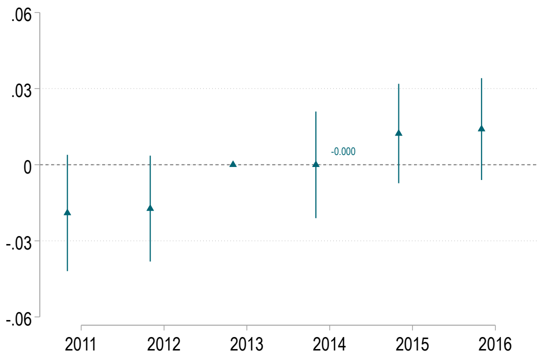
D. Enrollment in High Selective Programs

FIGURE 12. Impact of the RR Policy Disclosure on University Admission and Enrollment

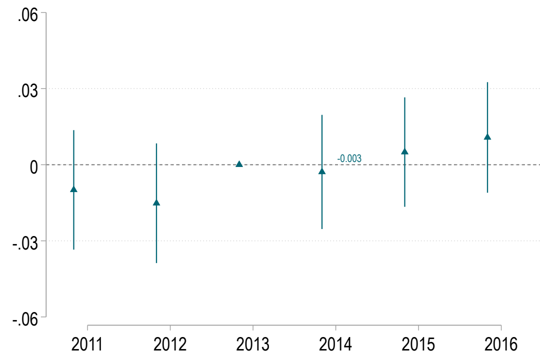
Note: This figure plots the coefficients from estimating equation (9) in the sample of students living in Santiago, where the outcome is an indicator for being accepted in a university (Panel A), enrolling in a university (Panel B), being accepted in a highly selective program (Panel C) and enrolling in a highly selective program (Panel D) and the key regressors are the interactions between having a positive gain and event-year dummies. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year. All the regressions include GPA deciles fixed effects. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, 99% confidence intervals are shown. Stars represent whether the coefficient of interest (dummy for year 2014 interacted with the dummy of having a positive gain) is statistically significant at 99% (***), 95% (**), or 90% (*).

students with a positive potential gain are 2.6 p.p. less likely to graduate on time (p-value = 0.05), suggesting that although these students ultimately complete their degrees, they require additional time to adjust academically, consistent with a catching-up effect.

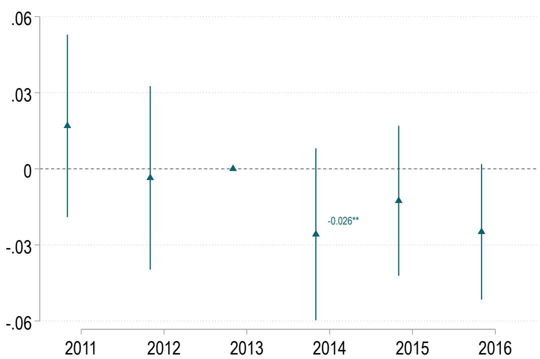
Figure A15 reports complementary evidence based on a sample restricted to students who take the national standardized test to apply to college in the year immediately following high school graduation. I find that students with a positive potential gain are, on average, 2.4 p.p. more likely to switch schools during twelfth grade. The magnitude of the



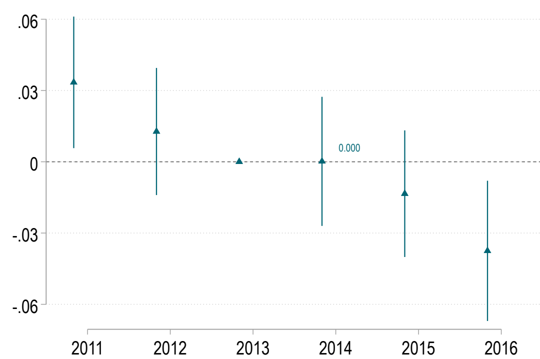
A. Dropout (first year)



B. Dropout (first two years)



C. Graduation on Time



D. Graduation

FIGURE 13. Impact of the RR Policy Disclosure on Dropout and Graduation Outcomes

Note: This figure plots the coefficients from estimating equation (9) in the sample of students living in Santiago, where the outcome is an indicator for dropping out during the first year student enrolled in a university (Panel A), dropping out during the first two years (Panel B), graduating on time (Panel C) and graduating (Panel D) and the key regressors are the interactions between having a positive gain and event-year dummies. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year. All the regressions include GPA deciles fixed effects. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, 99% confidence intervals are shown. Stars represent whether the coefficient of interest (dummy for year 2014 interacted with the dummy of having a positive gain) is statistically significant at 99% (***), 95% (**), or 90% (*).

estimated effect closely mirrors the baseline estimates in Figure (7), indicating that the strategic switching behavior documented earlier is also present among the population applying to college.

Using these results, together with the causal effects of a positive potential gain on college-related outcomes estimated above, I can recover the Local Average Treatment Effect (LATE) for the group of students who switched schools in response to the RR policy release. I do so by computing the ratio of the reduced form—obtained by regressing the instrument (having a positive potential gain) on college-related outcomes—to the first stage, which regresses the same instrument on an indicator equal to one if the student switched schools during twelfth grade.

Overall, my results suggest that students who switched schools during twelfth grade in response to the RR policy release increased their likelihood of being accepted into and enrolling in highly selective programs by 54 p.p. and 55 p.p., respectively. However, these students are 108 p.p. less likely to graduate on time relative to students who did not switch schools.

7. Effect on Policy Effectiveness

I now examine the distributional effects of students' strategic school switching by simulating student–major matches under two scenarios: one allowing school switching and another in which no student switches schools. Focusing on the cohort applying to college for the 2015 academic year, I show that students whose mothers have less than a high school diploma are negatively affected by switches, experiencing 30 percent lower acceptance rates into Tier-1 universities relative to the counterfactual in which no student switches schools. In contrast, students whose mothers have at least a college degree benefit from these movements, with higher acceptance rates into the most selective institutions. A similar pattern emerges by school type with the number of students admitted to the two most selective universities declining by 1.7 percent due to the equilibrium effects of school switching.

7.1. Simulating Application Scores and Matching Algorithm

To assess the distributional effects of students' strategic responses to the RR policy disclosure on university admissions, I simulate application scores for students applying in the 2015 admission cycle under two scenarios: one in which students remain in their initial high school in twelfth grade and one in which they graduate from the school in which they complete twelfth grade. For each scenario, I compute students' application scores and implement the Deferred Acceptance (DA) algorithm to determine admission outcomes. This simulation-based approach allows me to isolate how strategic school switching reshapes the distribution of admitted students within the cohort exposed to strategic behavior.

I use this methodology to analyze the distributional effects of strategic switching for two main reasons. First, the RR policy timeline and other policy changes coincide in previous years makeing it harder to use any type of difference-in-difference event study design (see Figure A6 and Kapor, Karnani, and Neilson (2024)). Second, I am interested on the overall distributional effects of strategic responses, whereas any design such as regression discontinuity would only capture the effect on marginal students.

To implement the simulations, I calculate each student's application score under three scenarios. First, I compute RR and application scores assuming the student graduates from the school in which they began twelfth grade. Second, I compute these scores assuming the student graduates from the school in which they complete twelfth grade. In both cases, application scores change only through differences in RR scores, under the assumption that students' GPA and PSU scores are unaffected by school relocation. Patterns in the timing of school switching indicate that most students spend less than a full academic year in their destination school, which limits concerns about changes in GPA or PSU scores following relocation (see Figure 5). Finally, I compute application scores using the pre-policy weights from the 2012 admission cycle, which serve as the baseline for evaluating changes in the composition of admitted students.

Using the three application scores for each student, I compare outcomes under two counterfactual scenarios: one in which strategic switching is allowed (the observed equilibrium) and one in which no student switches schools. I measure changes in admissions as the percentage difference in the number of students from a given group admitted to each program in 2015 relative to 2012, both with and without school switching. Each change is calculated as follows:

(11)
$$\Delta^{Benchmark}_{g,2015,d} = 100 * \left(\frac{\text{\# students accepted with no students switched schools}_{g,2015,d}}{\text{\# students accepted using 2012 weights}_{g,2015,d}} - 1\right),$$

and

$$(12) \qquad \Delta^{Switches}_{g,2015,d} = 100 * \left(\frac{\text{\# students accepted with students relocation}_{g,2015,d}}{\text{\#students accepted using 2012 weights}_{g,2015,d}} - 1\right),$$

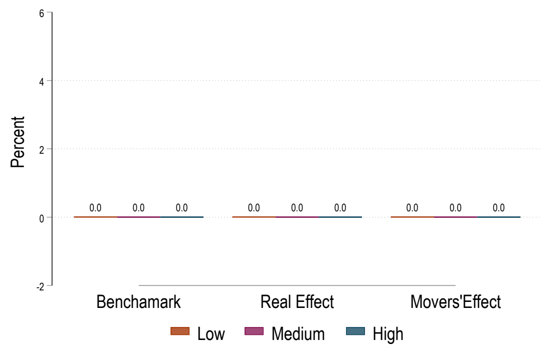
where $\Delta^{Benchmark}_{g,2015,d}$ is the change in the number of students belonging group g, accepted for the AY 2015 into program d relatively to the acceptance rate for the AY 2012 in the situation where no students would have switched schools, while $\Delta^{Switches}_{g,2015,d}$ is the change in the number of students belonging group g, accepted for the AY 2015 into program d relatively to the acceptance rate for the AY 2012 when some students switched schools.

7.2. Assignments and Distributional Effects under the Simulation Analysis

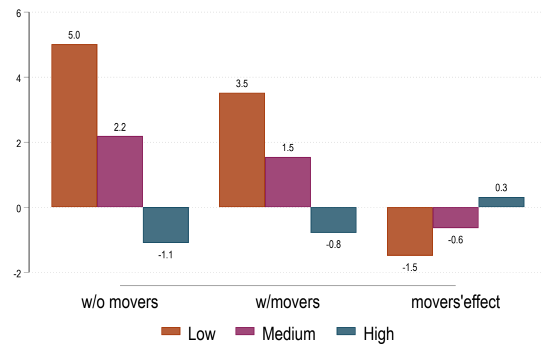
The Relative Ranking (RR) policy was designed to expand college access for students from lower socioeconomic backgrounds, who are disproportionately enrolled in public and lower-performing high schools (see section 2.3). Figure 14 reports simulated distributional effects by socioeconomic status, focusing on overall college admission (Panel A) and admission to Tier 1 universities (Panel B). This exercise shows that strategic school switching has little effect on aggregate college admissions. However, when considering acceptance rate at *Tier 1* universities, the policy had a smaller effect than it could have if students did not switch schools. Thus, strategic responses push out 1 out of 3 disadvantaged student.

Figures A16 and A17 show analogous patterns by school type and school performance. Strategic responses slightly reduce the number of students admitted from public schools system-wide, with a bigger impact in Tier 1 institutions (a decline of 1.7 percent), while effects by school performance are close to zero in both margins. These results align with prior evidence of modest average impacts of the RR policy shortly after its introduction, before its incentives were fully internalized by students Larroucau, Ríos Uribe, and

Mizala Salces (2015).



A. Overall System



B. Tier 1 Universites

FIGURE 14. Distributional Effects of Strategic Responses to the RR Policy Disclosure by Students Socioeconomics

Note: This figure plots the changes in acceptance from Equation (11) and Equation (12) for the overall system (Panel A) and tier 1 universities (Panel B). Each column represents the change in the number of students accepted by their mothers' education. First three columns report the change in the acceptance rate if studensts were not allowed to switch schools relatively to the pre-policy acceptance rates, the next three columns the change in the acceptance rate when students switched relative to the pre-policy acceptance rates, finally the last three columns show the effect of the strategic switches in the acceptance rate. Each column includes was estimated using the cohort of students applying to to college for the AY 2015.

7.3. Discussion

Many affirmative action policies in higher education define eligibility using students' high schools. This approach is motivated by the close relationship between school quality, school type (public, charter, or private), and students' socioeconomic backgrounds. However, researchers and policymakers should be cautious when evaluating such policies. Policies *targeting* students from some particular high schools could create incentives to game the policy.

Figure A18 illustrates this issue in the Chilean context. Strategic responses by school switching alters the distribution of students across schools in ways that attenuate the intended effects of the RR policy. As a result, evaluating the policy based solely on students' graduation schools can lead to an incomplete picture of its impact. In my setting, estimates that rely on graduation school rather than pre-policy school affiliation tend to overstate the policy's effects by 100% as they do not account for changes in school composition.

8. CONCLUSION

This paper provides evidence that changes in centralized college admission systems can generate strategic responses by students during high school that attenuate the intended effects of policy reforms. Focusing on Chile's relative ranking–based affirmative action policy, I show that students respond strategically to incentives tied to their graduating high school by relocating in twelfth grade. These endogenous school switches reduce the policy's effectiveness in expanding access for disadvantaged students by approximately 30

The results indicate that strategic responses are concentrated among students attending high-performing schools and among those whose parents held high educational aspirations. These students systematically targeted destination schools in ways that increased their college application scores, consistent with the incentives embedded in the policy design. I further show that students who switched schools were more likely to enroll in highly selective majors, although they were also less likely to graduate on time. To identify these effects, I introduce a novel instrument based on each student's potential gain from switching schools within their relevant market.

Finally, using simulation-based counterfactuals, I show that strategic school switching reshapes the distribution of admitted students—especially in the most selective universities—thereby weakening the policy's intended distributional impact. These results highlight an important implication for policy evaluation: analyses that rely on students' graduation schools may overstate policy effects by ignoring endogenous changes in school composition. More broadly, the findings underscore the importance of accounting for behavioral responses when designing and evaluating affirmative action policies based on school-level eligibility.

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Appendix A. Additional Figures and Tables

TABLE A1. High Schools' Characteristics by School Performance (2010-2013)

	Public Schools					Voucher Schools					Non-Voucher Private Schools				
	Overall	Q_1	Q_2	Q_3	Q_4	Overall	Q_1	Q_2	Q_3	Q_4	Overall	Q_1	Q_2	Q_3	Q_4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
***Panel 1:** Infraestructure*															
Classroom size	33.32	29.80	33.36	33.37	37.60	32.91	31.70	33.98	33.90	34.58	23.43	20.28	23.59	25.96	25.87
	(9.33)	(8.17)	(9.30)	(8.51)	(9.08)	(8.68)	(9.58)	(6.93)	(7.57)	(7.34)	(7.14)	(6.83)	(5.90)	(5.45)	(5.70)
Students/Teachers ratio	15.06	12.70	15.51	16.84	17.52	9.52	11.78	11.03	9.43	7.94	4.91	5.22	4.71	4.92	5.45
	(15.87)	(6.99)	(7.09)	(29.45)	(8.53)	(6.67)	(7.46)	6.95	(6.42)	(4.85)	(9.08)	(5.35)	(4.50)	(4.22)	(16.94)
***Panel 2:** Population served*															
Share of students from same county	0.76	0.79	0.75	0.78	0.73	0.74	0.69	0.74	0.77	0.76	0.67	0.62	0.66	0.69	0.72
	(0.24)	(0.19)	(0.25)	(0.23)	(0.27)	(0.25)	(0.28)	(0.25)	(0.22)	(0.22)	(0.25)	(0.24)	(0.26)	(0.25)	(0.24)
Father hhold head ratio	0.56	0.55	0.57	0.56	0.57	0.56	0.54	0.56	0.56	0.58	0.70	0.62	0.68	0.73	0.77
	(0.13)	(0.16)	(0.12)	(0.11)	(0.10)	(0.12)	(0.15)	(0.11)	(0.11)	(0.10)	(0.16)	(0.17)	(0.15)	(0.14)	(0.12)
Mom education < HS ratio	0.69	0.77	0.75	0.70	0.56	0.44	0.66	0.50	0.38	0.25	0.06	0.10	0.07	0.05	0.04
	(0.23)	(0.18)	(0.19)	(0.20)	(0.26)	(0.29)	(0.25)	(0.27)	(0.27)	(0.23)	(0.10)	(0.13)	(0.10)	(0.08)	(0.08)
Had internet at home ratio	0.47	0.40	0.41	0.46	0.58	0.69	0.51	0.65	0.75	0.84	0.97	0.96	0.98	0.98	0.99
	(0.21)	(0.20)	(0.20)	(0.20)	(0.21)	(0.23)	(0.23)	(0.21)	(0.18)	(0.14)	(0.06)	(0.07)	(0.04)	(0.04)	(0.03)
Hope student go to university ratio	0.44	0.32	0.37	0.43	0.64	0.69	0.45	0.63	0.77	0.89	0.95	0.89	0.96	0.98	0.99
	(0.20)	(0.13)	(0.14)	(0.15)	(0.20)	(0.23)	(0.19)	(0.19)	(0.16)	(0.10)	(0.10)	(0.10)	(0.05)	(0.03)	(0.02)
***Panel 3:** Ex-post results*															
mean $\underline{r}_s$	5.42	5.34	5.40	5.40	5.53	5.51	5.34	5.43	5.55	5.70	5.85	5.61	5.80	5.94	6.05
	(0.18)	(0.13)	(0.16)	(0.16)	(0.21)	(0.23)	(0.17)	(0.18)	(0.18)	(0.19)	(0.24)	(0.21)	(0.18)	(0.15)	(0.16)
mean $\bar{r}_s$	6.43	6.34	6.40	6.43	6.55	6.49	6.32	6.45	6.54	6.65	6.67	6.47	6.67	6.77	6.79
	(0.26)	(0.25)	(0.24)	(0.25)	(0.25)	(0.26)	(0.28)	(0.24)	(0.21)	(0.18)	(0.24)	(0.29)	(0.17)	(0.10)	(0.11)
College admission test mean score	554.39	549.04	552.78	553.55	562.06	557.11	545.68	549.57	558.81	572.73	588.11	563.85	581.96	597.07	607.48
	(20.97)	(20.65)	(20.20)	(20.48)	(19.90)	(22.13)	(20.95)	(19.26)	(18.02)	(19.33)	(25.77)	(23.24)	(20.28)	(16.89)	(17.44)
College admission test takers ratio	0.66	0.55	0.60	0.67	0.82	0.85	0.67	0.83	0.91	0.97	0.97	0.95	0.98	0.98	0.99
	(0.22)	(0.21)	(0.21)	(0.19)	(0.17)	(0.20)	(0.24)	(0.18)	(0.13)	(0.07)	(0.06)	(0.07)	(0.04)	(0.06)	(0.02)
Applying to college/Take PSU ratio	0.20	0.11	0.13	0.18	0.36	0.39	0.15	0.26	0.42	0.64	0.73	0.53	0.71	0.81	0.87
	(0.18)	(0.09)	(0.09)	(0.13)	(0.21)	(0.25)	(0.12)	(0.16)	(0.19)	(0.19)	(0.23)	(0.23)	(0.20)	(0.17)	(0.14)
Accepted in top 2 colleges ratio	0.02	0.01	0.01	0.02	0.04	0.04	0.02	0.03	0.04	0.08	0.23	0.12	0.18	0.27	0.35
	(0.07)	(0.06)	(0.04)	(0.06)	(0.09)	(0.09)	(0.10)	(0.07)	(0.07)	(0.09)	(0.22)	(0.20)	(0.18)	(0.19)	(0.23)
Accepted in colleges ranked 3-10 ratio	0.27	0.25	0.29	0.24	0.29	0.26	0.22	0.23	0.25	0.31	0.27	0.23	0.27	0.29	0.29
	(0.27)	(0.32)	(0.30)	(0.24)	(0.21)	(0.22)	(0.30)	(0.21)	(0.19)	(0.18)	(0.18)	(0.20)	(0.18)	(0.16)	(0.18)
Number of high schools	**756**	**177**	**205**	**188**	**186**	**1447**	**342**	**358**	**354**	**393**	**353**	**81**	**86**	**93**	**93**

Note: This table reports schools main characteristics by type by performance using year cohorts graduating from high school between 2010-2013. Columns (1) to (5) reports average characteristics for public high schools, where the last 4 columns divide the sample of schools by performance. Columns (6) to (10) reports average characteristics for voucher high schools, where the last 4 columns divide the sample of schools by performance. Columns (11) to (15) reports average characteristics for non-voucher private high schools, where the last 4 columns divide the sample of schools by performance

TABLE A2. Preferences Rankings in the Submitted Lists for Academic Year 2013

	Fraction reporting	Fraction admitted
	(1)	(2)
Choice 1	1.000	0.429
Choice 2	0.933	0.196
Choice 3	0.831	0.123
Choice 4	0.627	0.069
Choice 5	0.454	0.051
Choice 6	0.316	0.038
Choice 7	0.221	0.030
Choice 8	0.156	0.022
Choice 9	0.106	0.019
Choice 10	0.078	0.016
Nb. students	118,208	95,300

Note: This table reports average characteristics of Chilean college applicants for the 2013 academic year, by preference rank. Column (1) shows the share of applications corresponding to each choice rank, and Column (2) reports the share of students admitted for each choice.

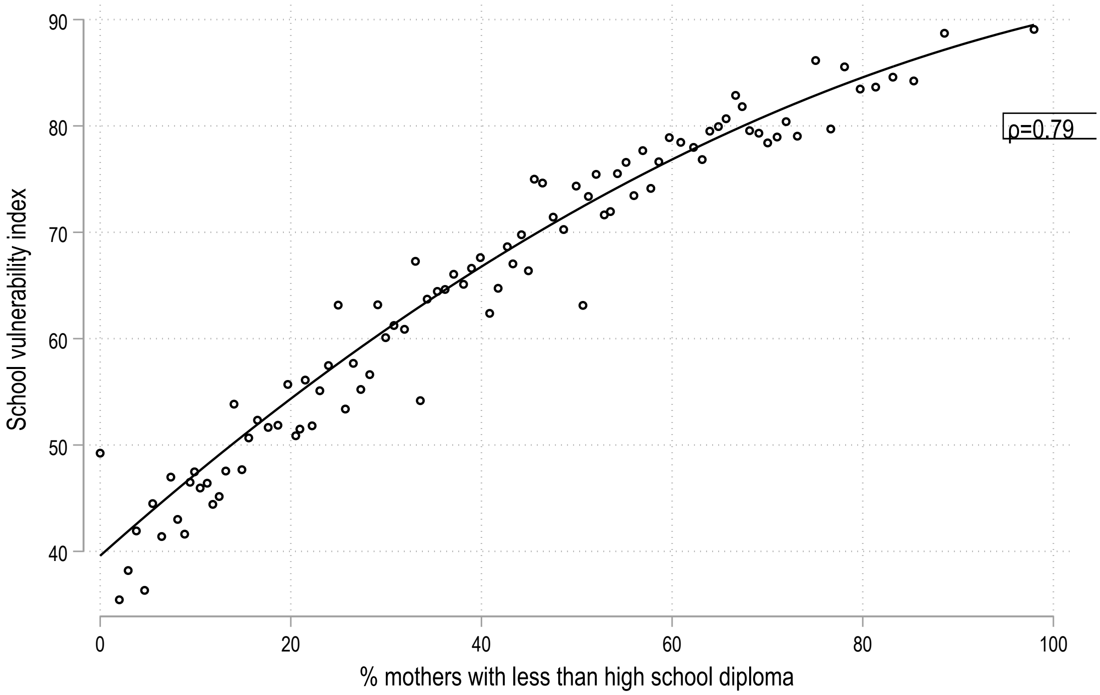


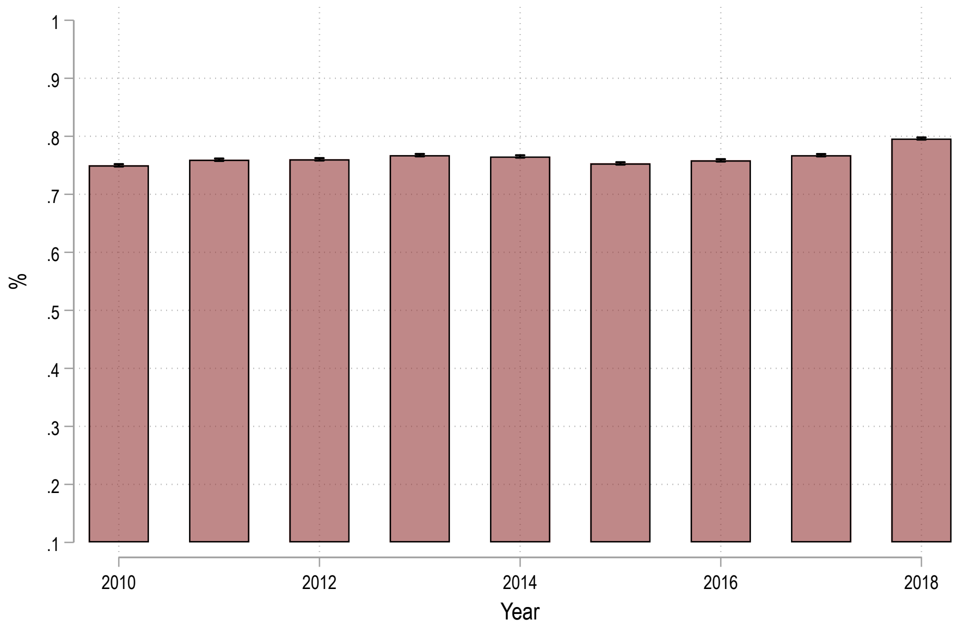
FIGURE A1. School vulnerability index & students SES

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.

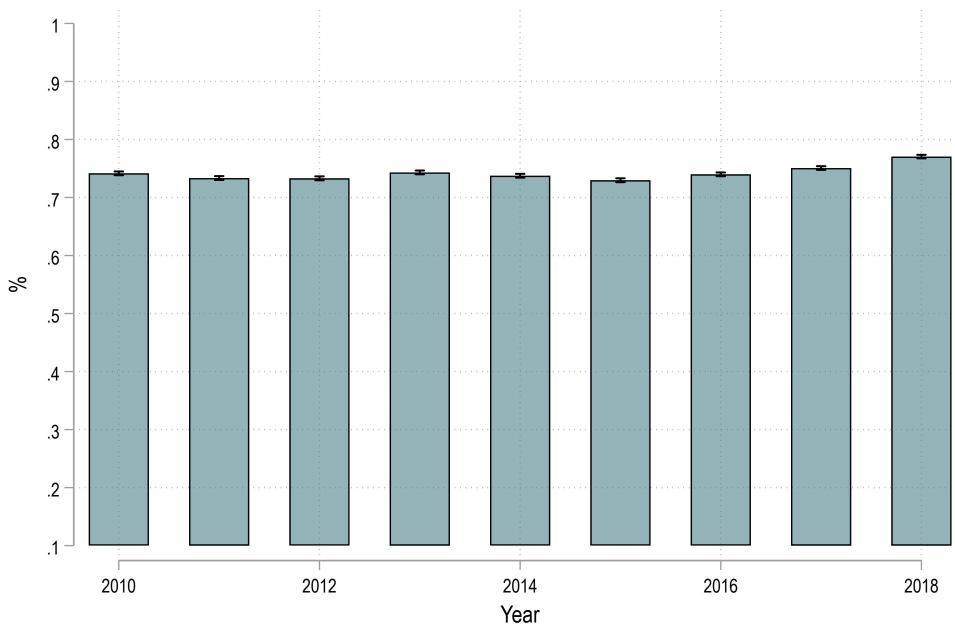
TABLE A3. High schools in Santiago's main characteristics (2010-2013).

	Public Schools					Voucher Schools					Non-Voucher Private Schools				
	Overall	Q_1	Q_2	Q_3	Q_4	Overall	Q_1	Q_2	Q_3	Q_4	Overall	Q_1	Q_2	Q_3	Q_4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
***Panel 1:** Infraestructure*															
Classroom size	34.50	31.28	33.84	34.25	38.26	34.23	33.81	35.08	34.65	36.00	23.71	19.33	23.71	27.24	26.83
	(7.32)	(6.19)	(7.19)	(6.48)	(7.18)	(7.80)	(7.64)	(6.71)	(6.71)	(6.51)	(7.78)	(7.04)	(6.43)	(5.02)	(6.11)
Students/Teachers ratio	15.67	13.14	16.92	15.61	18.03	10.49	14.02	12.27	9.85	7.94	5.14	5.70	4.27	5.23	6.57
	(8.13)	(6.44)	(7.57)	(8.72)	(8.52)	(7.22)	(7.93)	7.61	(6.85)	(4.53)	(11.93)	(7.17)	(1.49)	(4.90)	(24.35)
***Panel 2:** Population served*															
Share of students from same county	0.58	0.67	0.57	0.59	0.43	0.65	0.60	0.62	0.70	0.66	0.58	0.51	0.60	0.61	0.60
	(0.31)	(0.21)	(0.33)	(0.32)	(0.33)	(0.29)	(0.32)	(0.30)	(0.26)	(0.27)	(0.23)	(0.19)	(0.23)	(0.24)	(0.24)
Father hhold head ratio	0.52	0.52	0.54	0.52	0.52	0.56	0.54	0.55	0.56	0.58	0.69	0.58	0.65	0.73	0.76
	(0.11)	(0.13)	(0.11)	(0.09)	(0.09)	(0.11)	(0.11)	(0.10)	(0.11)	(0.09)	(0.17)	(0.17)	(0.15)	(0.15)	(0.13)
Mom education < HS ratio	0.63	0.73	0.72	0.63	0.43	0.43	0.63	0.49	0.38	0.26	0.05	0.08	0.06	0.04	0.03
	(0.24)	(0.18)	(0.19)	(0.23)	(0.26)	(0.29)	(0.24)	(0.27)	(0.26)	(0.23)	(0.09)	(0.11)	(0.08)	(0.06)	(0.07)
Had internet at home ratio	0.57	0.47	0.51	0.59	0.74	0.74	0.59	0.70	0.79	0.86	0.98	0.96	0.97	0.99	0.99
	(0.19)	(0.16)	(0.18)	(0.16)	(0.14)	(0.18)	(0.17)	(0.16)	(0.14)	(0.12)	(0.05)	(0.06)	(0.04)	(0.02)	(0.02)
Hope student go to university ratio	0.46	0.32	0.37	0.45	0.72	0.66	0.43	0.59	0.74	0.86	0.95	0.87	0.96	0.98	0.99
	(0.21)	(0.11)	(0.13)	(0.14)	(0.20)	(0.22)	(0.18)	(0.15)	(0.15)	(0.11)	(0.11)	(0.11)	(0.05)	(0.02)	(0.02)
***Panel 3:** Ex-post results*															
mean $\underline{r}_s$	5.34	5.27	5.30	5.31	5.52	5.43	5.27	5.36	5.47	5.62	5.82	5.58	5.76	5.91	6.04
	(0.18)	(0.09)	(0.14)	(0.13)	(0.23)	(0.22)	(0.16)	(0.15)	(0.16)	(0.20)	(0.25)	(0.19)	(0.17)	(0.16)	(0.18)
mean $\bar{r}_s$	6.42	6.32	6.41	6.43	6.54	6.45	6.30	6.43	6.49	6.59	6.64	6.42	6.63	6.76	6.77
	(0.24)	(0.22)	(0.24)	(0.21)	(0.23)	(0.25)	(0.28)	(0.22)	(0.20)	(0.19)	(0.25)	(0.28)	(0.15)	(0.09)	(0.13)
College admission test mean score	542.74	538.46	539.05	538.51	557.46	549.14	537.65	542.03	551.17	564.82	585.82	561.09	578.38	594.69	608.60
	(19.13)	(16.80)	(16.91)	(14.04)	(22.08)	(20.38)	(18.29)	(16.82)	(16.24)	(18.62)	(26.53)	(21.85)	(19.14)	(17.26)	(18.73)
College admission test takers ratio	0.72	0.62	0.68	0.73	0.89	0.85	0.68	0.84	0.92	0.97	0.97	0.94	0.98	0.97	0.99
	(0.19)	(0.19)	(0.16)	(0.16)	(0.12)	(0.18)	(0.21)	(0.15)	(0.10)	(0.05)	(0.07)	(0.07)	(0.03)	(0.08)	(0.01)
Applying to college/Take PSU ratio	0.19	0.08	0.09	0.13	0.42	0.30	0.11	0.18	0.31	0.53	0.68	0.44	0.64	0.77	0.85
	(0.21)	(0.11)	(0.07)	(0.09)	(0.27)	(0.21)	(0.09)	(0.11)	(0.15)	(0.19)	(0.24)	(0.20)	(0.21)	(0.19)	(0.16)
Accepted in top 2 colleges ratio	0.06	0.02	0.03	0.04	0.12	0.08	0.04	0.05	0.07	0.14	0.33	0.19	0.25	0.37	0.50
	(0.11)	(0.13)	(0.07)	(0.10)	(0.13)	(0.11)	(0.14)	(0.08)	(0.08)	(0.11)	(0.23)	(0.24)	(0.18)	(0.18)	(0.20)
Accepted in colleges ranked 3-10 ratio	0.23	0.21	0.25	0.22	0.24	0.22	0.21	0.21	0.22	0.25	0.21	0.18	0.23	0.22	0.19
	(0.24)	(0.32)	(0.29)	(0.23)	(0.12)	(0.19)	(0.28)	(0.19)	(0.15)	(0.11)	(0.13)	(0.18)	(0.13)	(0.10)	(0.13)
Number of high schools	**195**	**45**	**54**	**51**	**45**	**566**	**133**	**139**	**138**	**156**	**192**	**47**	**45**	**51**	**49**

Note: This table reports schools main characteristics by type by performance using year cohorts graduating from high school between 2010-2013. Columns (1) to (5) reports average characteristics for public high schools, where the last 4 columns divide the sample of schools by performance. Columns (6) to (10) reports average characteristics for voucher high schools, where the last 4 columns divide the sample of schools by performance. Columns (11) to (15) reports average characteristics for non-voucher private high schools, where the last 4 columns divide the sample of schools by performance



A. Chile



B. Santiago

FIGURE A2. Share of students living in the same county during primary and secondary school

Note: This figure presents the share of students living in the same county during primary school and secondary school. Primary school location is calculated using the grade in which the student is first observed, while secondary school location is measured in grade twelve. Each bar represents the yearly share, and vertical lines indicate their corresponding confidence intervals.

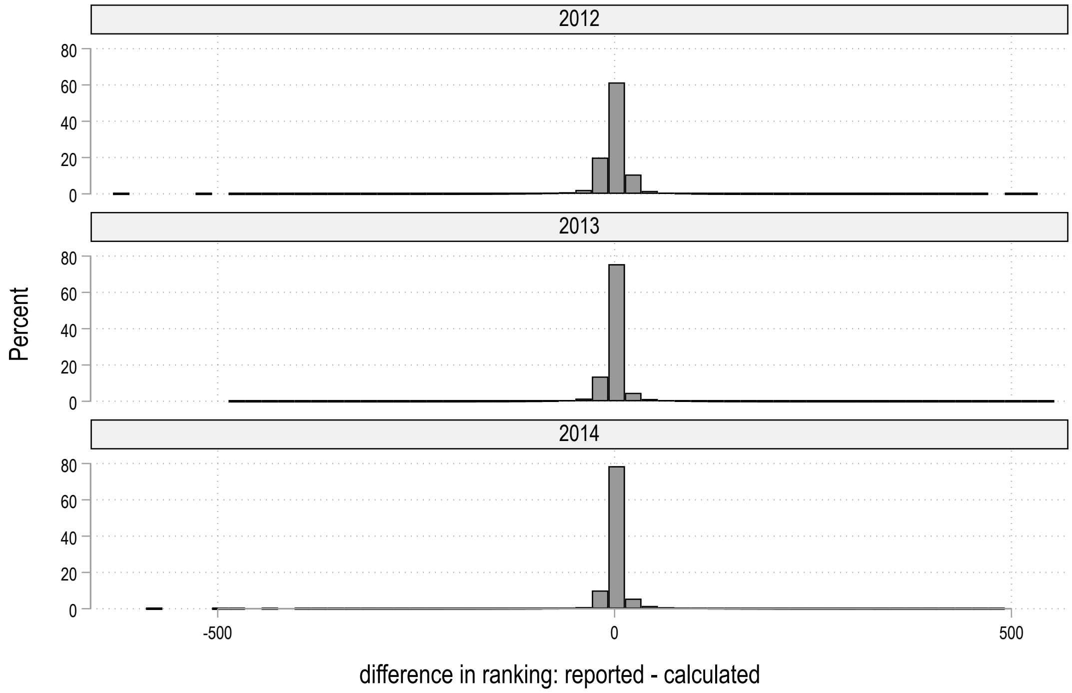


FIGURE A3. Difference between reported ranking score and calculated ranking score.

Note: This figure presents the distribution of the difference between the reported ranking in adminsitrative records from DEMRE, and the calculated ranking using the formula and the public records.

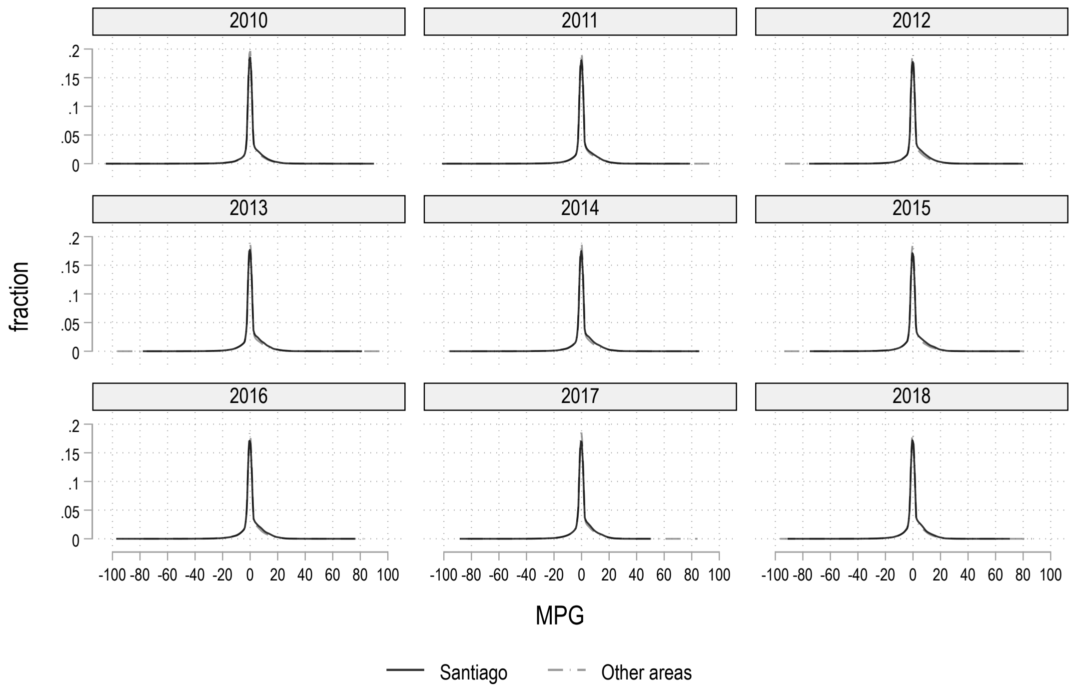


FIGURE A4. Potential gain's distribution by year and area.

Note: This figure presents distribution of MPG by year and area between 2010 and 2018. The solid line shows the distribution for the main metropolitan area, Santiago, while the dash line represents the distribution for the rest of the country.

A. Within-school GPA Controls

B. Standardized Test Controls

FIGURE A5. Impact of the RR policy disclosure on students' switching schools at the beginning of twelfth grade

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching schools at the beginning of twelfth grade and the key regressors are the interactions between having a positive gain and event-year dummies. Panel A includes fixed effects for within-school GPA deciles, while Panel B includes fixed effects for tenth-grade standardized test deciles. The event of interest is the release of the RR policy formula in November 2013. The sample includes cohorts of students entering twelfth grade each year in the entire country. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

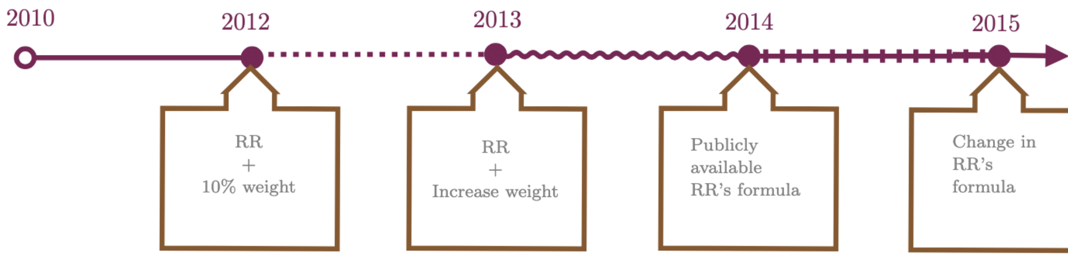
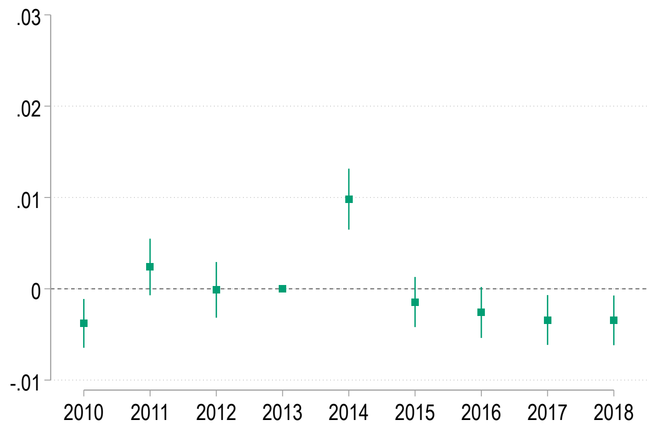
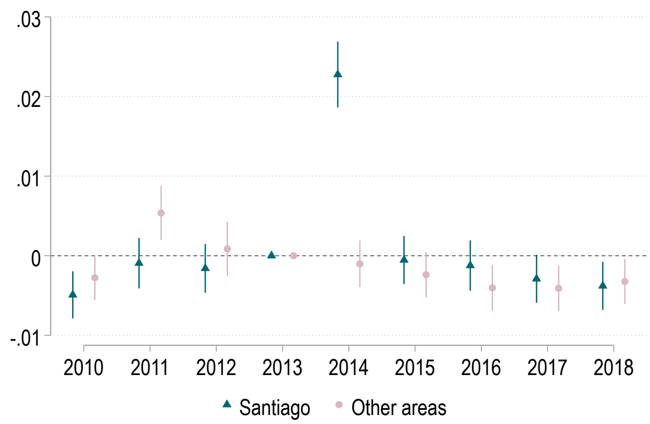


FIGURE A6. Relative ranking policy's timeline

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.



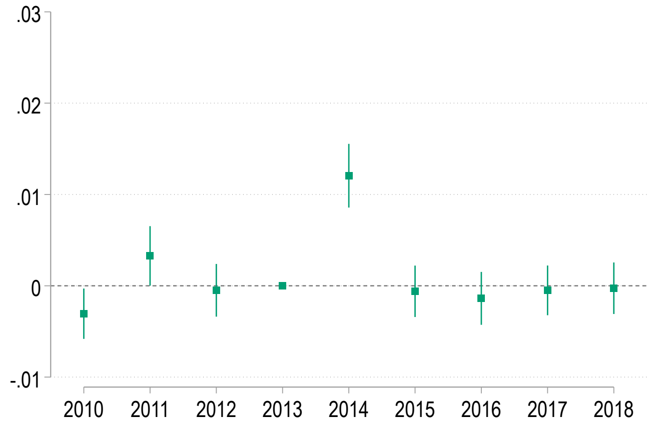
A. Chile



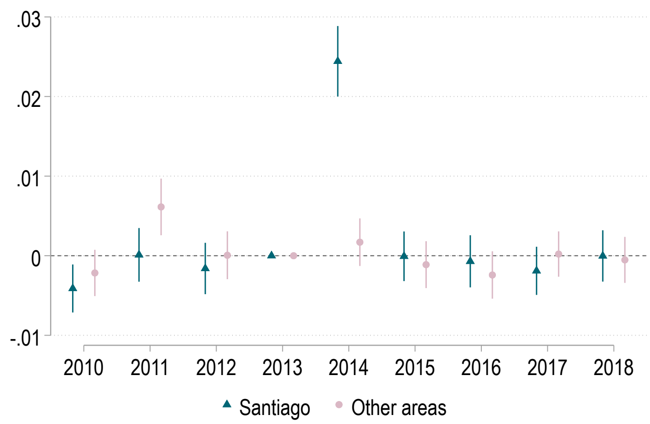
B. Santiago

FIGURE A7. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower Threshold Schools

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school with a lower mean threshold ($\underline{r}$) in twelfth grade and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



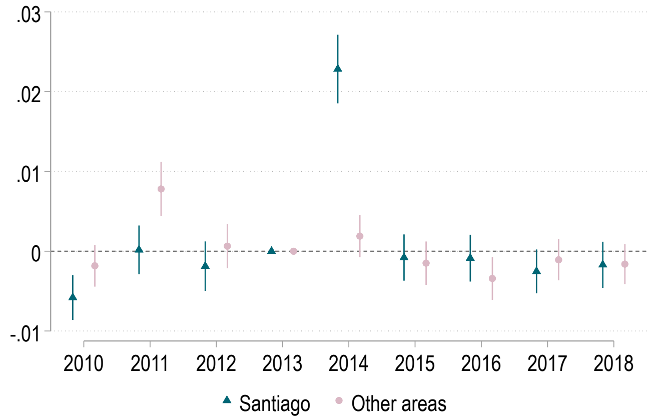
A. Chile



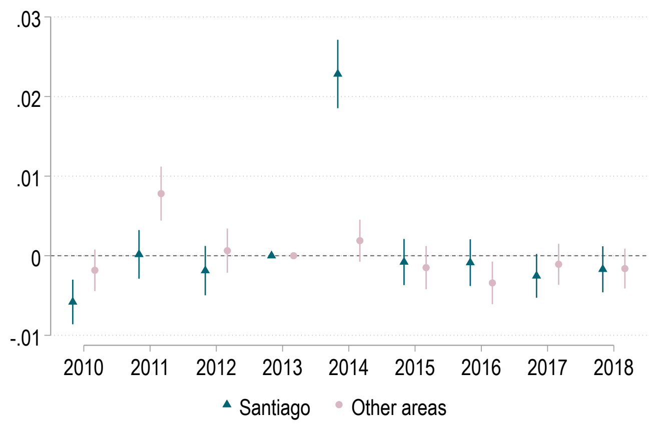
B. Santiago

FIGURE A8. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower National Test Score Schools

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school with a lower national test score mean in twelfth grade, and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



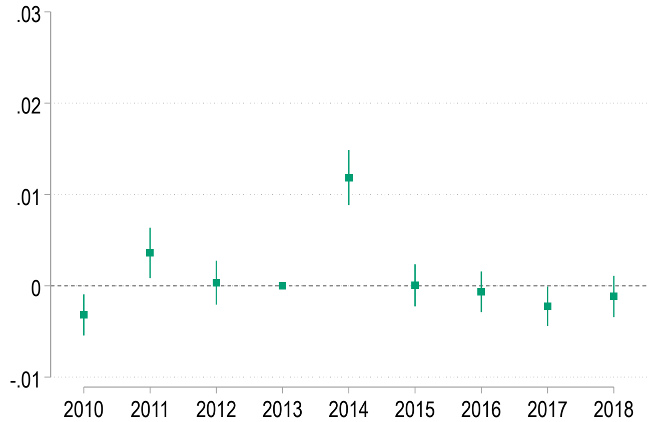
A. Chile



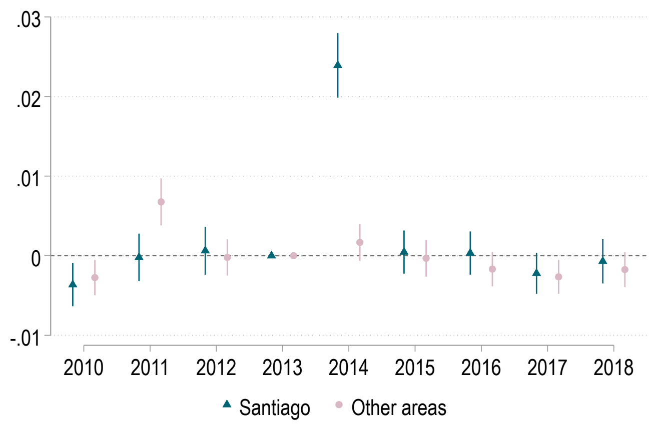
B. Santiago

FIGURE A9. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower College-Sending Schools

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school with a smaller number of students attending college, and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



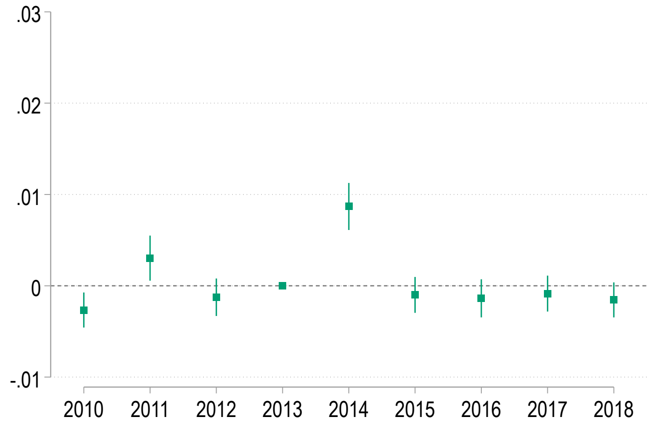
A. Chile



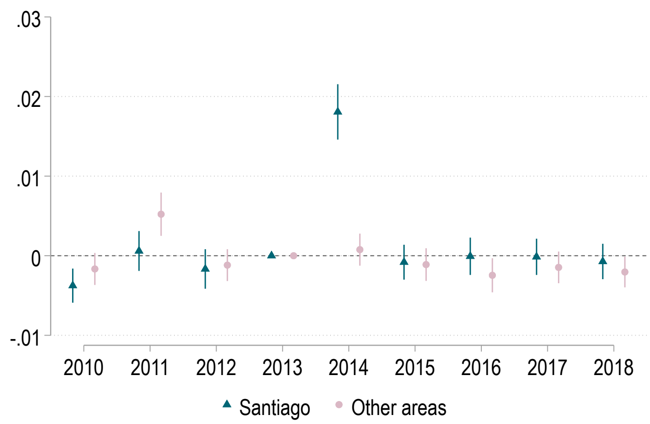
B. Santiago

FIGURE A10. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower Tier-One-College-Sending Schools

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school with a smaller number of students attending tier 1 college, and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



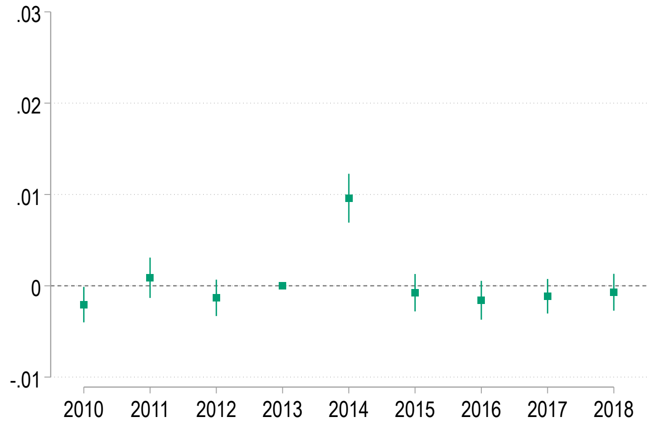
A. Chile



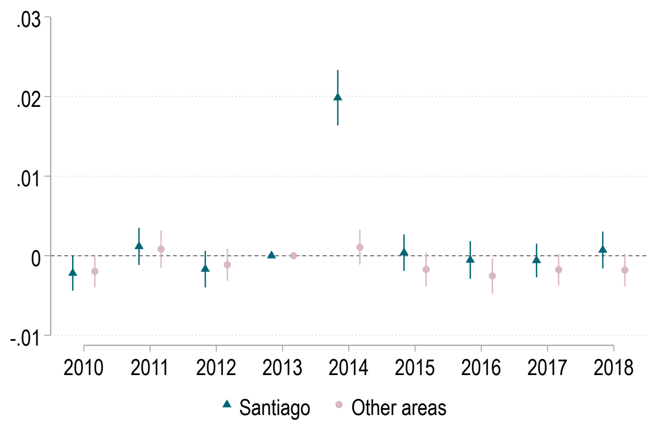
B. Santiago

FIGURE A11. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower Performing Schools

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school with a lower performance, and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



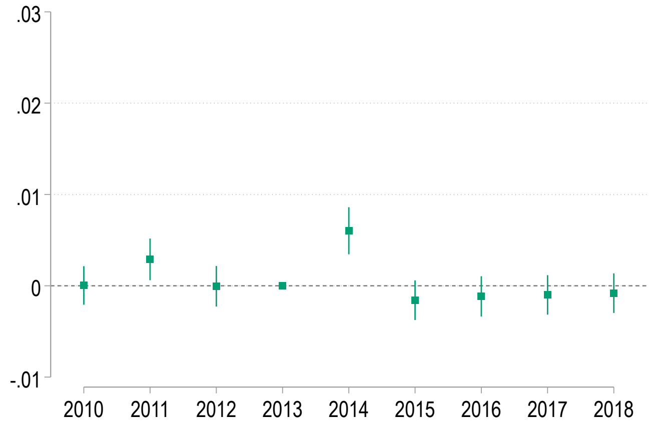
A. Chile



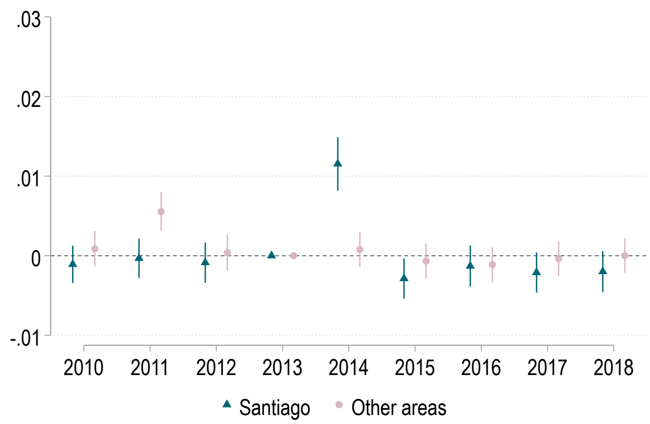
B. Santiago

FIGURE A12. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Schools with More Disadvataged Students

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school with a higher share of students from lower socioeconomic groups, and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



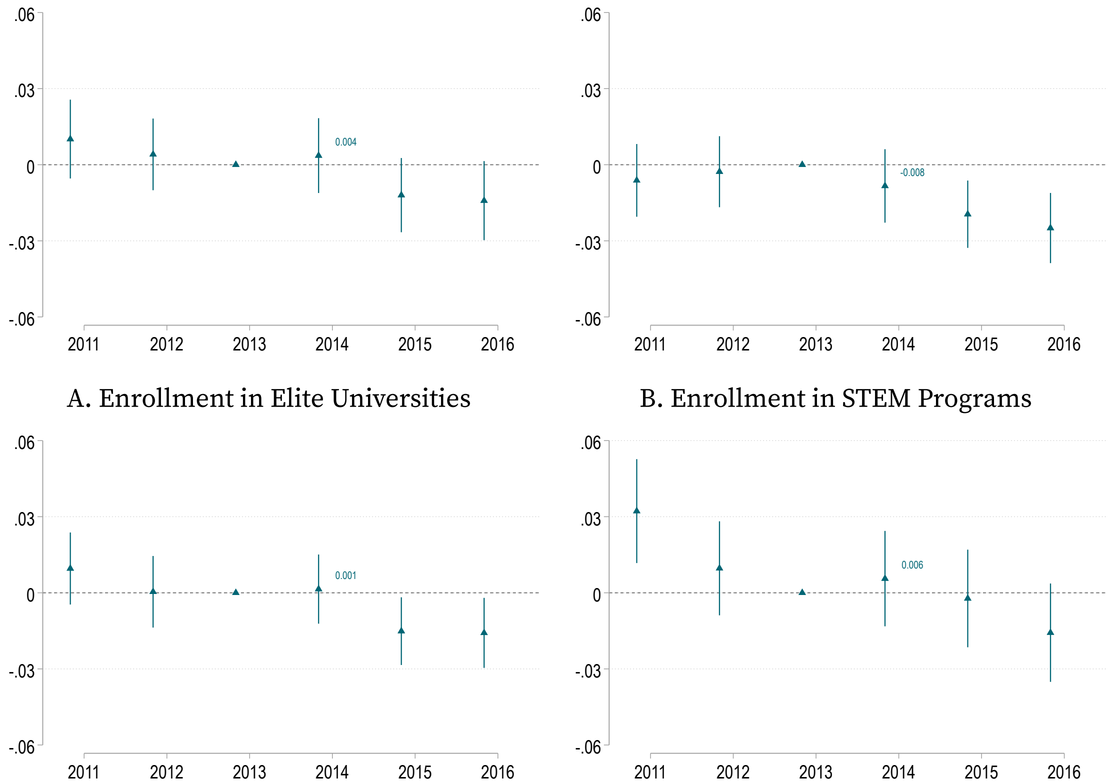
A. Chile



B. Santiago

FIGURE A13. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Schools Closer to Home

Note: This figure plots the coefficients from estimating equation (9), where the outcome is an indicator for switching to a school closer to their residences, and the key regressors are the interactions between having a positive potential gain and event-year dummies. Both panels include fixed effects for within-school GPA deciles. Panel A presents the estimation nationwide, while in Panel B equation (9) is estimated separately for students living in Santiago (blue triangles) and students living in other areas (pink circles). The event of interest is the release of the RR policy formula in November 2013. The sample includes all cohorts of twelfth-grade students nationwide. The y-axis reports the change in the probability relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



A. Enrollment in Elite Universities

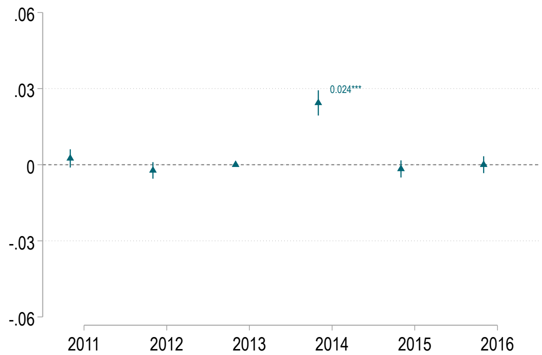
B. Enrollment in STEM Programs

C. Enrollment in *Traditional* Programs

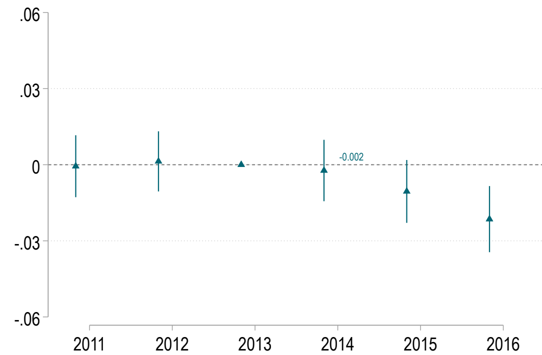
D. Enrollment in High Return Programs

FIGURE A14. Impact of the RR Policy Disclosure on University Admission and Enrollment

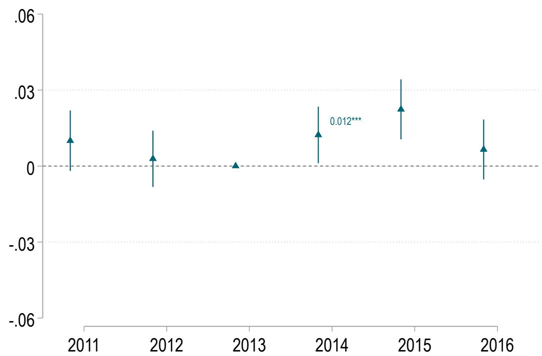
Note: This figure plots the coefficients from estimating equation (9) in the sample of students living in Santiago, where the outcome is an indicator for enrolling in an elite university (Panel A), a STEM program (Panel B), a traditional program (Panel C), and a high return program (Panel D) and the key regressors are the interactions between having a positive gain and event-year dummies. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students entering twelfth grade each year. All the regressions include GPA deciles fixed effects. The y-axis reports the change in the probability relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, 99% confidence intervals are shown. Stars represent whether the coefficient of interest (dummy for year 2014 interacted with the dummy of having a positive gain) is statistically significant at 99% (***), 95% (**), or 90% (*).



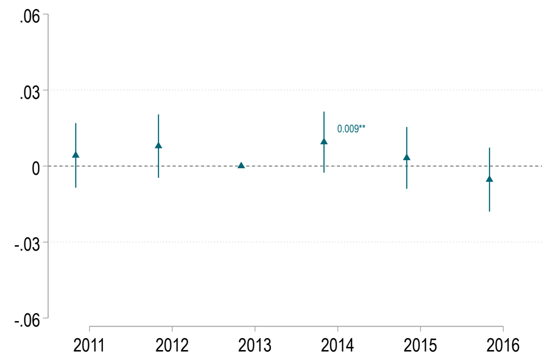
A. Switching in 12th grade



B. Application to at Least One Program



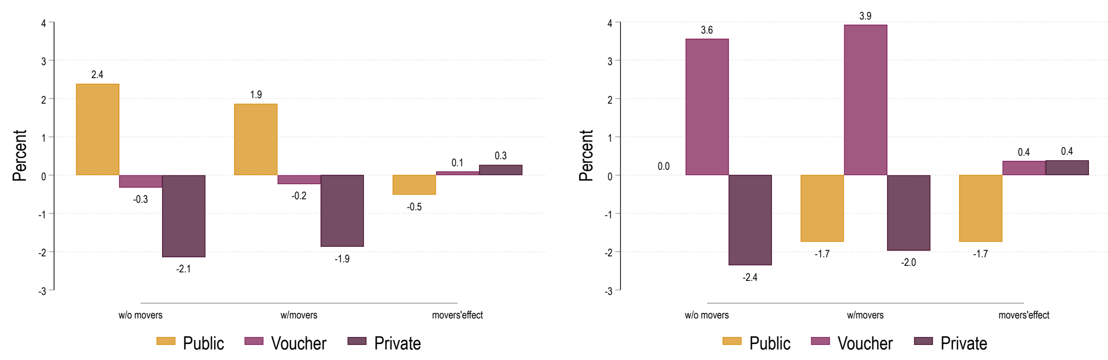
C. Application: Elite University



D. Application: Highly Selective Program

FIGURE A15. Impact of the RR Policy Disclosure Switching High Schools and Application to College for the Sample of Applicants

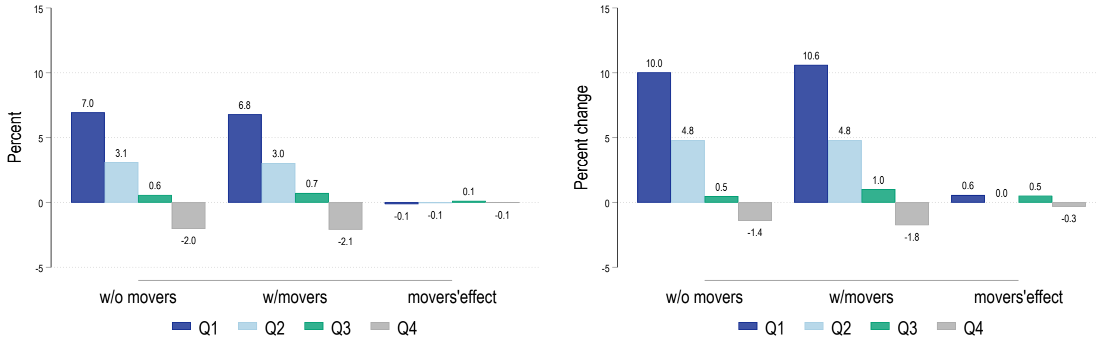
Note: This figure plots the coefficients from estimating equation (9) in the sample of students living in Santiago, where the outcome is an indicator for switching schools (Panel A), applying to at least one progra (Panel B), applying to a program in an elite university within the three most preferred degrees (Panel C), and applying to a highly selective program within the three most preferred degrees (Panel D) and the key regressors are the interactions between having a positive gain and event-year dummies. The event of interest is the release of the RR policy formula in November 2013. Each sample includes cohorts of students graduating from twelfth grade each year. All the regressions include GPA deciles fixed effects. The y-axis reports the change in the probability relative to 2013 (the omitted year). Standard errors are clustered at the school-market level, 99% confidence intervals are shown. Stars represent whether the coefficient of interest (dummy for year 2014 interacted with the dummy of having a positive gain) is statistically significant at 99% (***), 95% (**), or 90% (*).



A. Overall System B. Tier 1 Universites

FIGURE A16. Distributional Effects of Strategic Responses to the RR Policy Disclosure by Type of School

Note: This figure plots the changes in acceptance from Equation (11) and Equation (12) for the overall system (Panel A) and tier 1 universities (Panel B). Each column represents the change in the number of students accepted by type of school they started twelfth grade. First three columns report the change in the acceptance rate if studensts were not allowed to switch schools relatively to the pre-policy acceptance rates, the next three columns the change in the acceptance rate when students switched relative to the pre-policy acceptance rates, finally the last three columns show the effect of the strategic switches in the acceptance rate. Each column includes was estimated using the cohort of students applying to to college for the AY 2015.

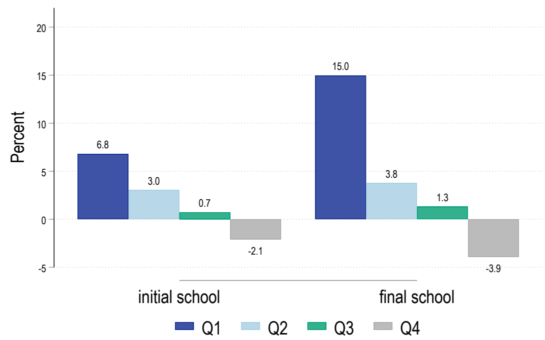


A. Overall System

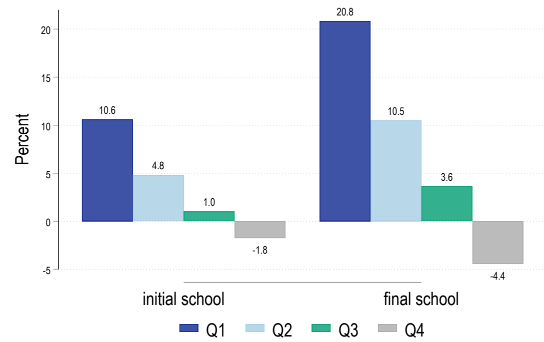
B. Tier 1 Universites

FIGURE A17. Distributional Effects of Strategic Responses to the RR Policy Disclosure by School Performance

Note: This figure plots the changes in acceptance from Equation (11) and Equation (12) for the overall system (Panel A) and tier 1 universities (Panel B). Each column represents the change in the number of students accepted by the performance of the school they started twelfth grade. First four columns report the change in the acceptance rate if students were not allowed to switch schools relatively to the pre-policy acceptance rates, the next four columns the change in the acceptance rate when students switched relative to the pre-policy acceptance rates, finally the last four columns show the effect of the strategic switches in the acceptance rate. Each column was estimated using the cohort of students applying to to college for the AY 2015.



A. Overall System



B. Tier 1 Universites

FIGURE A18. Relative Ranking Policy Impact Considering Starting and Ending Schools performance

Note: This figure plots the changes in acceptance from Equation (11) and Equation (12) for the overall system (Panel A) and tier 1 universities (Panel B). Each column represents the change in the number of students accepted by school performance. First four columns report the change in the acceptance rate by school performance considering all students graduate from the same school they started twelfth grade, the next four columns calculate the same changes but grouping students by the school they graduated from. Each column was estimated using the cohort of students applying to to college for the AY 2015.

Appendix B. 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.[34] 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).[35]

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

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

public in November,[36] 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 C. 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 **??** 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

[36] 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 **??**.

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 3.3, 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 3.3 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 3.3, 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 3.3 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 3.3:

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

Notice that one of the two last lines are *effective* for any combination of application score in school H and L.[37] Suppose $d_H = 1$, then the capacity constraint is

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

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.

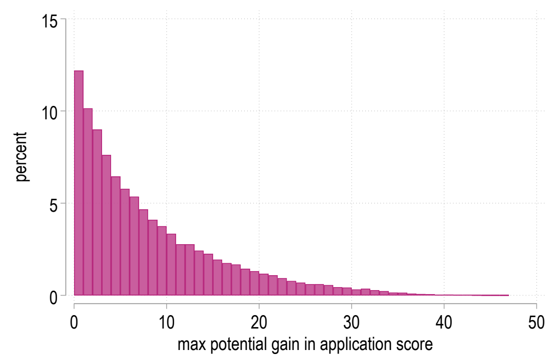
Finally, suppose a fraction q of students with a potential gain in switching, have a cost of switching higher than the value of college. Then only that fraction of students switch schools, and therefore the pool of accepted students into college change in a ratio equal to $1 - q$.

□

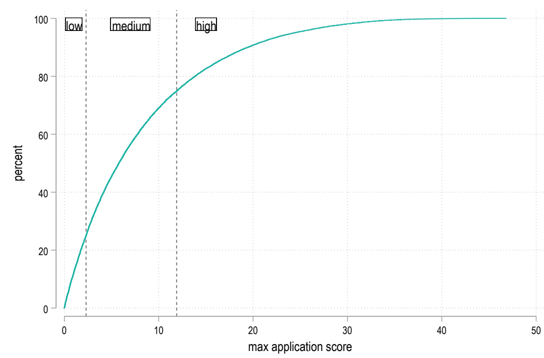
[37] It is not possible to have $AS_L(x) > AS_H(x)$ for a value x and simultaneously $AS_L(x) < AS_H(x)$.

Appendix D. 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 A19 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 A19. Potential score gain, 4 km buffer (2010-2013).

Note: .

Appendix E. Analysis using sample of students living in the same county than in primary school

In this appendix, I re-estimate my main results using only the sample of students who report living in the same county at the beginning of twelfth grade as they did during primary school. Figures A20 present the impact of the RR policy disclosure (the event of interest) on students' switching schools decision using equation (9).

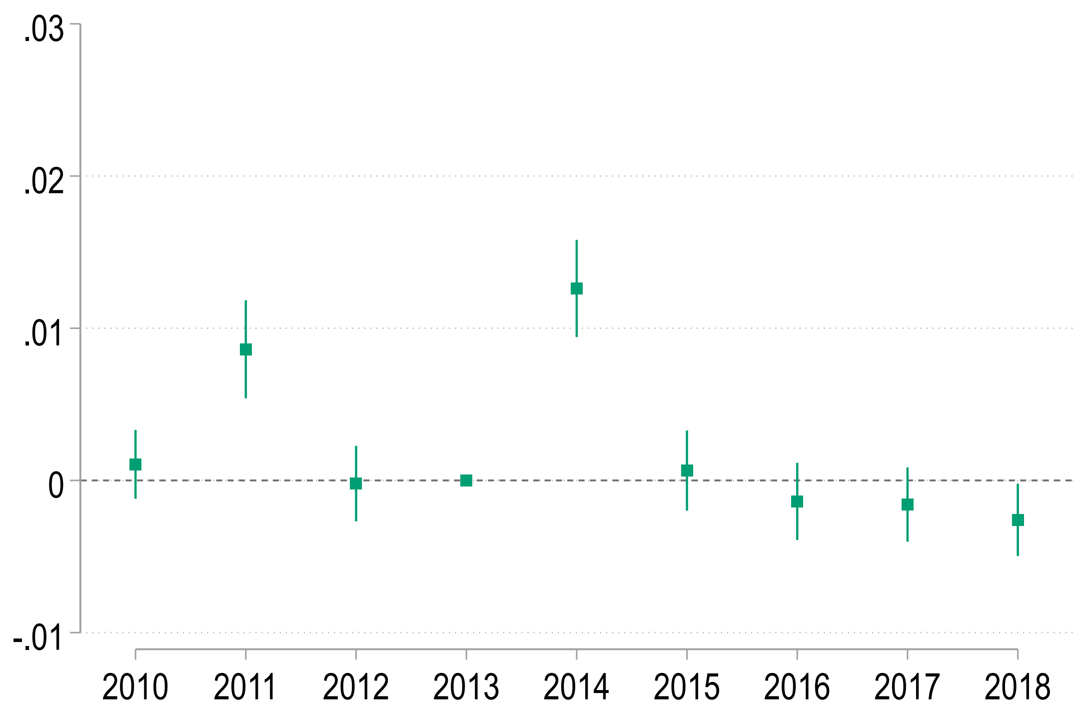


FIGURE A20. Impact of the RR policy disclosure on students' switching schools during twelfth grade for the sample of students always living in the same county

Note: This figure plots the coefficients from the regression of students' switching schools in twelfth grade on the interaction between having a positive potential gain and event-year dummies using equation (9). The event of interest is the release of the RR policy's formula in November 2013. The sample consists of a cohort of students in the entire country starting twelfth grade each year who report living in the same county at the beginning of twelfth grade as they did in primary school. The y-axis shows the change in the probability of the outcome relatively to 2013 (the omitted category). Standard errors are clustered at the students' school market level, and 99% confidence intervals are displayed.