Strategic Responses to College Admission Policies: Evidence from Chile

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This paper shows that progressive college admission policies based on students' school can be weakened by strategic pre-college behavior. Leveraging the disclosure of a ranking-based affirmative action policy in Chile and administrative data covering all senior high school students nationwide, I find that students with scope to benefit strategically are 63% more likely to transfer high schools during twelfth grade than similar students without such gains. These students are more likely to enroll in selective college majors but less likely to graduate on time. Simulation-based counterfactuals show that strategic switching reduces admissions of disadvantaged students to selective universities by approximately 30%.

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College attendance is a key channel for upward mobility across developed and developing countries (Chetty, Deming, and Friedman 2026; 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 in the highest income quantiles (Chetty et al. 2020; Michelman, Price, and Zimmerman 2022; Zimmerman 2019). In Latin America, for instance, only 16% of students enrolled in tertiary education in 2023 fell within the poorest income quintile—a share nearly 30 percentage points (p.p.) smaller than that of students in 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 higher education access for students from historically disadvantaged groups.[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] Such policies are designed to promote equity by reallocating admission opportunities toward underrepresented students. When eligibility is based on immutable characteristics such as race, strategic responses are limited. However, when eligibility depends on characteristics students can influence—such as which high school they attend, their neighborhood of residence, or their income bracket—the policy may create incentives for non-targeted students to adjust their pre-college choices to qualify for preferential treatment, absent any change in effort or academic investment. Such strategic responses could weaken the intended distributional effects by reshaping which students ultimately benefit.

This paper shows that the intended effects of progressive college admission policies based on students' school 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 of low

[1] Such policies include preferential admissions (e.g., quotas, affirmative action; Otero, Barahona, and Dobbin 2021; Antonovics and Backes 2014; Kapor 2025), financial aid (Solis 2017; Burland et al. 2023), information 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] Approximately 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). In Texas, for example, the top 10% of students from each high school can attend any public university in the state (Antonovics and Backes 2014; Kapor 2025); Brazil implemented federal university quotas (Mello 2023; Otero, Barahona, and Dobbin 2021); and Chile adopted a policy comparing students' grade point averages (GPAs) to historical trends within their high school (Larroucau, Ríos Uribe, and Mizala Salces 2015; Reyes 2022) and offering direct access for high-performing low-income students (Tincani et al. 2021).

socioeconomic status (SES) 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. The public information release affected students in two key ways: It made salient that college application scores depended on students' relative performance within high schools and created incentives to transfer *at the last moment* to schools where students could improve their relative ranking—and thus their perceived admission chances—with no changes to their 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 her rank relative to the previous three graduating cohorts at her school. Although the 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 admission score.

The Chilean setting is especially well suited for the study of 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 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

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

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

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

whether students transfer schools in twelfth grade, to distinguish transfers at the beginning of the academic year from those during the year, and to compute the RR 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 SES from 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 subsequent college admission and enrollment outcomes.

I divide the analysis into three parts. First, I develop a simple theoretical framework in which students decide whether to transfer high schools, taking 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. Relative ranking–based policies are more effective at increasing acceptance rates for students from low-performing schools when school switching is costly.[7] Moreover, because of the formula's nonlinearity, incentives to switch are concentrated among students whose GPA is in neither the lower nor the upper tail of the distribution at high-performing schools, where higher historical thresholds generate larger potential gains from graduating elsewhere.

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. Exploiting variation in students' potential gains from the policy and a difference-in-differences event-study design, I show that the public 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 p.p. more likely to transfer in 2014 than in the prepolicy period, corresponding to a 63% increase over the predisclosure mean. This effect is driven entirely by students in Santiago, where a positive potential gain increases the likelihood of school switching by 2.4 p.p.—approximately 530 additional strategic transfers in a single cohort—, a 140% increase over the prepolicy mean. Monthly data further show that these transfers occurred disproportionately toward the end of the academic year—when strategic switching is most valuable and least costly.[8]

[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 10-grade standardized average test score.

[8] The magnitude of this response exceeds that documented by Cullen, Long, and Reback (2013) in the context of Texas'

Within Santiago, responses are concentrated among more advantaged students. In particular, students whose parents held high educational aspirations were 3.2 p.p. more likely to transfer schools following the public information release, and students attending high-performing high schools were 4.5 p.p. more likely to switch during twelfth grade.

I then examine how these strategic responses translate into postsecondary outcomes. Focusing on students living in Santiago, the area driving the national results, I find that 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 p.p. more likely to enroll in highly selective programs and 2.6 p.p. less likely to graduate on time, suggesting that strategic school switching increased access to more selective programs at the cost of slower academic progression.

The third part of the paper studies the effect of strategic switching on the policy's intended distributional effects. I exploit the structure of the application score formula and 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. Under the current policy, low-SES students are 3.5% more likely to be admitted to selective colleges. Absent strategic switching, however, this effect would reach 5%, implying that strategic responses reduce the policy's potential effectiveness by more than 30%.

This study makes two main contributions. First, I contribute to a growing literature on unintended consequences of educational policies. Previous research has shown that college admission policies affect pre-college outcomes such as effort (Grau 2018; Bodoh-Creed and Hickman 2018; Tincani et al. 2021; González and Johnson 2018), attendance and dropout (Akhtari, Bau, and Laliberté 2024; Cáceres-Delpiano, Giolito, and Castillo 2018), exam performance (Antonovics and Backes 2014; Bleemer 2021; Laajaj, Moya, and Sánchez 2022), and school choice (Cullen, Long, and Reback 2013; Mello 2023; Estevan, Gall, and Morin 2019). I advance this work along three dimensions. First, by linking administrative data on the universe of high school seniors to centralized college application, enrollment, and graduation records, I trace students from pre-college switching decisions through

Top Ten Percent plan, where 211 students per cohort strategically chose less competitive high schools statewide—despite that setting requiring families to commit to a school years in advance. The lower cost of switching in the Chilean context, where students can transfer mid-year during twelfth grade, is consistent with a larger behavioral response.

post-secondary outcomes. I show that switchers gained access to more selective programs but were less likely to graduate on time. Second, I exploit Chile's centralized admissions algorithm to simulate student–major matches under a no-switching counterfactual, providing an estimate of how strategic behavior erodes a policy's distributional effects. Third, my identification uses the admission formula to compute each student's score gain from graduating at an alternative school, rather than relying on noisy ability proxies or area-level measures of policy exposure.

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 2022; Harris and Mills 2021; Kapor 2025; Long, Saenz, and Tienda 2010) and has examined their distributional effects (Otero, Barahona, and Dobbin 2021; Bleemer 2021; Black, Denning, and Rothstein 2023; Mello 2023; 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 by approximately 30% for disadvantaged students at selective universities.

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. Research documents that students' ordinal rank affects their 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 than those in lower-performing schools despite having identical GPAs. This feature incentivizes transfer to lower-performing schools to improve admission prospects.

The rest of the paper is organized as follows. Section 1 describes the institutional setting. Section 2 introduces a stylized model rationalizing the incentives for students to switch schools and their equilibrium effects. Section 3 presents the data, descriptive statistics, and construction of main variables. Section 4 outlines the identification strategies. Section 5 presents the empirical results. Section 6 presents the counterfactual analysis. Section 7 concludes.

1. CONTEXT: FROM SECONDARY TO HIGHER EDUCATION IN CHILE

Chile is a middle-income country with persistently high income and educational inequality.[9] 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.

1.1. 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 (Arias Ortiz et al. 2024). 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.[10] 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.[11] 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 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

[9] 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.

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

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

tertiary education, compared with only 25% from the lowest quintile.[12] The link between students' SES, 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.[13] Advocates for reform argued that students from low-quality schools face significantly lower chances of attending college—regardless of their individual ability or academic performance—due to 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 1.3 for details).

1.2. 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.[14]

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.[15] Second, they must take the national college entrance exam (PSU),[16] which is administered annually in mid- to late December.[17] Third, applicants submit an ordered list of up to ten preferred college–major combinations. To support families in this process, the organization overseeing centralized

[12]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 (Arias Ortiz et al. 2024).

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

[14]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-Fernández (2022) and Larroucau and Rios (2020) for more details.

[15]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.

[16]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.

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

admissions (DEMRE) maintains an official website with comprehensive information on procedures, timelines, and participating institutions.[18]

Applicants to the centralized system are matched to programs using a deferred acceptance (DA) algorithm.[19] A key theoretical property of the DA mechanism is that it is strategy-proof: listing programs truthfully is a dominant strategy, as higher-priority applicants can displace lower-ranked ones in later rounds (Abdulkadiroğlu et al. 2020; Dubins and Freedman 1981; Roth 1982). However, this property assumes students are allowed to rank all programs without restriction (Haeringer and Klijn 2009; Pathak and Sönmez 2013).

Table 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.

1.3. 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

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

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

between GPA and the standardized RR score. In the figure, $\underline{r}_s$ denotes the average GPA across the three previous cohorts, and $\bar{r}_s$ the maximum GPA within those cohorts. I use the same notation throughout the paper.

For students to respond strategically, the policy must be salient. I review all documents available on the college application system's official website and in newspapers to establish when the information was made public. Although the policy was implemented in 2012,[20] 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 this rule would apply to the current academic year as well. Starting in 2015, the government reformed the RR to weight scores across all schools attended, limiting the gains from last-minute switches.

Two additional pieces of evidence support the claim that the formula was not salient before November 2013. First, none of the official documents published prior to that date make any reference to how students' GPAs were compared across schools—the very feature that creates the incentive to switch. Second, press coverage of strategic responses to the ranking policy appears only in 2014, after the formula had been disclosed, with no earlier reporting on this channel.[21] While neither of these constitutes direct survey evidence on families' information sets, together they are consistent with the identifying assumption that the formula disclosure marked a discrete shift in the ability of students to act on the policy's incentives.

1.4. 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. 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

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

[21] See, for example, Radio Universidad de Chile, "Preparan cambios al controvertido ranking de notas," January 1, 2015.

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,[22] these institutions dominate the region's top positions, reinforcing their reputation as the most selective and prestigious in the country.

2. 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 switching 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.

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.

2.1. Application Scores

Suppose there are two high schools, L and H, and two colleges: a selective college and a less selective college. A fraction μ_H of students attend school H, and the remaining $\mu_L = 1 - \mu_H$ attend school L. Each high school e is characterized by two predetermined, publicly known parameters: a mean threshold $\underline{r}_e$ and a maximum threshold $\bar{r}_e$.

Students have already been assigned to a high school, and their only decision is whether to switch. 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

[22] 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.

the switching decision. Each student is characterized by a GPA $g_i \in (\underline{g}, \bar{g})$ and an initial high school $s \in \{L, H\}$.[23]

The selective college has capacity $K < 1$ and admits students based on their application scores; the remaining students enroll in the less selective college, which absorbs all remaining applicants. This structure reflects Chile's centralized admission system, in which students submit a ranked list of program.[24] Empirically, I show in Section 5 that the policy does not affect overall admission rates but shifts the composition of students across programs of different selectivity.

Before the policy, student *i*'s application score is a linear function of GPA:[25]

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

where γ is a slope parameter and θ is a constant. Both parameters are the same across all schools.

After the policy, the mapping from GPA to application scores depends on the school e from which the student graduates:

$$AS_e(g_i) = \begin{cases} \gamma g_i + \theta, & \text{if } g_i < \underline{r}_e, \\ \gamma_e g_i + \theta_e, & \text{if } \underline{r}_e \le g_i < \bar{r}_e, \\ 850, & \text{if } g_i \ge \bar{r}_e, \end{cases} \tag{2}$$

where γ_e and θ_e denote school-specific slope and intercept parameters, and 850 is the maximum possible score, with $\gamma_e > \gamma$. A student with rank below $\underline{r}_e$ receives the same score as under the pre-policy rule; a student with rank between $\underline{r}_e$ and $\bar{r}_e$ receives a school-specific bonus; and a student with rank above $\bar{r}_e$ receives the maximum score.

Figure 3 graphically illustrates the case in which school H has higher thresholds than school

[23] I assume that students' high school GPA and PSU scores are unaffected by the switching decision.

[24] The less selective college can be interpreted as the bundle of all other program–university pairs to which a student applies. Among applicants to Chile's centralized system, over 85% are admitted to one of the programs in their list through the centralized system. Moreover, Chile has a large number of universities and Institutos Profesionales outside the centralized system that serve as additional options for students who are not placed centrally. Together, these features imply that the relevant margin for the vast majority of applicants is which institution they attend, not whether they attend college at all.

[25] This formula follows the official conversion table published by MINEDUC. Note that the application score does not vary across schools in equation (1).

L.[26] A student starting twelfth grade in school s has a potential gain in their application score from switching to school e if

$$AS_{ie} \geq AS_{is},$$

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

2.2. Switching Decision

I build on the frameworks of Cullen, Long, and Reback (2013) and Estevan, Gall, and Morin (2019). A continuum of students of mass 1 applies from both schools and is placed into one of the two colleges. The selective college admits those above an equilibrium cutoff AS^*; the remaining students enroll in the less selective college.

A student admitted to the selective college derives utility $U_i^S > 0$ relative to the less selective college (normalized to zero).[27] Students pay a direct cost $c_{ise} \geq 0$ when switching from school s to school e and derive school-specific utility $b_{is} > b_{ie}$.[28] The student's utility from staying in school s is $V_{is} = b_{is} + U_i^S \cdot \mathbf{1}\{AS_s(g_i) \geq AS^*\}$, while the utility from switching to school e is $V_{ie} = b_{ie} - c_{ise} + U_i^S \cdot \mathbf{1}\{AS_e(g_i) \geq AS^*\}$. Because all students are placed into some college, the only case in which switching improves a student's outcome is when she is below the cutoff at school s but above it at school e: $AS_e(g_i) \geq AS^* > AS_s(g_i)$. In that case, switching is optimal if and only if

$$U_i^S \;\geq\; b_{is} - b_{ie} + c_{ise} \;\equiv\; \tilde{c}_i, \tag{3}$$

where $\tilde{c}_i$ bundles the school-attachment differential and the direct switching cost. The condition requires both that switching changes the admission outcome and that the selective-college premium exceeds the net cost.

[26] 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.

[27] U_i^S captures the premium from attending the selective college over the less selective college—for example, the difference in expected returns to a degree from an elite versus a non-elite institution.

[28] This is consistent with the fact that families chose school s at the beginning of secondary education.

2.3. Equilibrium and Policy Effects

Students' GPAs in schools H and L, before any switching, follow distributions $F_H(g)$ and $F_L(g)$, respectively. Let g_e^* denote the GPA that yields a score exactly equal to AS^* in school e. Two conditions characterize the equilibrium. First, the centralized system uses a single ranking with no quotas, so the cutoff is unique across schools:

(Unique Score) $$AS_L(g_L^*) \;=\; AS_H(g_H^*) \;=\; AS^*.$$

Second, the total mass of students admitted to the selective college must equal the available capacity:

(Capacity) $$\mu_L\big[1 - F_L(g_L^*)\big] \;+\; \mu_H\big[1 - F_H(g_H^*)\big] \;=\; K.$$

I now characterize the equilibrium under three scenarios.

PROPOSITION 1 (Equilibrium before the policy). *Under equation* (1)*, scores do not depend on school, so* $g_L^* = g_H^* = g_0^*$*. No student has an incentive to switch schools.*

The result is immediate: before the policy, $AS(g_i) = \gamma\, g_i + \theta$ regardless of school, so $AS_e(g_i) \geq AS^* > AS_s(g_i)$ can never hold and no student switches. Under $F_H = F_L$, each school fills a share of seats proportional to its population; under general distributions, school e's share is $\mu_e[1 - F_e(g_0^*)]/K$.

PROPOSITION 2 (Equilibrium after the policy without switching). *When the policy is implemented but students cannot switch, schools H and L generically have different GPA cutoffs for admission to the selective college:* $g_H^* \neq g_L^*$*. The share of students admitted to the selective college increases in the school with the lower cutoff and decreases in the other. The equilibrium cutoff rises:* $AS_1^* > AS_0^*$.

To build intuition, assume $\underline{r}_L < \underline{r}_H$ and $\bar{r}_L < \bar{r}_H$, as in Figure 3. Then $AS_L(g_i) \geq AS_H(g_i)$ for all g_i, so by (Unique Score) we have $g_L^* < g_H^*$: a lower GPA suffices at school L. The capacity constraint then implies that school L gains seats and school H loses them. Under $F_H = F_L$ this follows immediately; under general distributions, the result holds whenever the score function in school L weakly dominates that in school H, which the threshold ordering guarantees. The formal proof is in Appendix C.

PROPOSITION 3 (Equilibrium after the policy with switching). *When the policy is implemented and students are allowed to switch, the equilibrium cutoff rises further:* $AS_0^* \leq AS_1^* \leq AS_2^*$. *The effect of the policy on the composition of students in the selective college depends on how costly it is for students to switch.*

When switching is allowed, students satisfying (3) relocate to the school where the score function is more generous, pushing AS^* upward. When $\tilde{c}_i = 0$ for all students, every student with a positive gain switches and the policy's intended redistribution is fully undone. Students displaced from the selective college are pushed into the less selective college. When $\tilde{c}_i$ is prohibitively high, the outcome coincides with Proposition 2. The formal proof is in Appendix C. Note that with multiple selective colleges, full attenuation generically fails even when switching costs are zero, because switchers who upgrade across tiers couple the capacity constraints. The single-college case therefore provides an upper bound on the degree of policy undoing.

Testable predictions. The model generates three predictions. First, potential gains from switching are concentrated among students whose GPA falls in the bonus region of the application score function—between the school's mean and maximum thresholds, $\underline{r}_e$ and $\bar{r}_e$. Second, students from high-threshold schools are more likely to have a positive gain, because the low-threshold school's bonus region covers a wider range of GPAs. Third, a positive score gain is necessary but not sufficient for switching: the gain must move the student from the less selective college into the selective college, and the selective-college premium must exceed the cost of switching.

3. DATA

3.1. 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 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.

3.2. 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' 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 SES, 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 as 2 and 4-km buffers.[29] Figure A2 shows the share of students living in the same county

[29]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).

during primary and secondary school by year for Chile (panel A) and Santiago (panel B). Chile has 346 counties, and on average, 76.5% of students report living in the same county throughout their K–12 education, whereas in Santiago (56 counties) the corresponding share is approximately 74%. Both patterns are stable across years. Moreover, in Appendix E, I re-estimate my main analysis restricting the sample to students who remain in the same county throughout their schooling, and the results are robust.

3.3. 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 ($switch_{ism}$, 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 (with half of them switching during 12th grade). Nearly 45% of students live in Santiago, and 90% attend either 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.

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. 26% of applicants rank at least 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, 11% of the applicants are accepted into an elite university, and a similar share enrolled in that type of institution. Now, when considering university graduation, 22% of applicants graduate from a university on time.

In terms of student characteristics, applicants to universities participating in the centralized admission system exhibit stronger academic performance than the overall population of high school 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 (quartiles 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 into quality quartiles by type, based on average scores from the national standardized test taken by tenth-grade students in 2010.[30] Table A1 presents the main characteristics of each school type. A common pattern across school types is the positive correlation between GPA thresholds and standardized test performance: schools with higher SIMCE scores also set higher grading standards, with a pre-policy correlation of 0.7 (see Figure A3).

I. **Potential Gain**

A student's *potential gain* (PG) is the difference between the RR 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. I compute this gain for every school in the student's relevant market, defined as the set of high schools located within a 2 km radius of their primary school (see Section 3.2 for data limitations and Appendix D

[30] I also observe tenth-grade SIMCE scores for 2012 and 2014–2018. I use scores in 2010 to have the pre-policy measure.

for validations on how relevant markets are calculated).

I summarize each student's switching incentives using the *median* of these gains. The median captures whether a student faces a generally favorable environment for strategic switching, rather than depending on the existence of a single attractive option. This choice has two advantages. First, it is robust to outliers that may arise from measurement error in individual schools' thresholds or from schools that are geographically proximate but practically inaccessible due to enrollment constraints or track mismatch. Second, it does not require families to have detailed knowledge of every school in their market—a strong assumption given evidence that parents often hold imperfect information about available schools and their attributes (Hastings and Weinstein 2008; Kapor, Neilson, and Zimmerman 2020).

To compute these measures, I calculate the counterfactual ranking 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. Because the formula relies exclusively on predetermined variables (see Section 1.3 for details), I can calculate MPG for any cohort, including those that applied before the policy was implemented. Additionally, as robustness check, I re-estimate the main analysis using different measures of treatment in Appendix E. The results are robust to alternative definitions.

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 noise/proxy error in constructing MPG/markets is nondifferential with respect to unobserved determinants of switching/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 to 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. In Appendix F 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 RR 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 A4 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 form 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 plots the share of students with positive gain by year, and Figure A5 compares 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 1.3). 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

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

[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.

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 7,500 students transfer schools during their final year, with roughly one in two doing so during the academic year rather than before it starts. Students in Santiago account for about more than 40% of all transfers nationwide, displaying a similar temporal pattern to the national trend. Among high-performing schools (Panels C and D), 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 2).

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 after the RR policy formula was made public in November 2013. 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.

4. EMPIRICAL SPECIFICATION

This section outlines the identification strategy used in this paper. The main strategy (4.1 and 4.2), 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.

4.1. 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:

(4)

$$switch_during12_{istm} = \sum_{\tau=2010 \tau \neq 2013}^{2018} \beta_\tau \mathbb{1}\{t = \tau\} \cdot positive_gain_{ism} + \beta_{pg} positive_gain_{ism} + \delta_t + \delta_s + \delta_{g\,pa_decile} + \varepsilon_{istm},$$

where $switch_during12_{istm}$ 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 RR 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, $\delta_{g\,pa_decile}$ 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 across different points of the GPA distribution. With these fixed effects in place, identification comes from comparing students in the same school and the same GPA decile who differ in their median potential gain solely because their primary school locations place them in different local school markets.

To interpret the estimated coefficients as causal effects, two identifying assumptions must hold. First, there should be no differential pretrends 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 4 identifies the causal effect of the policy disclosure on students' strategic decision to switch schools.

4.2. University Application, Admission, and Enrollment

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

$$college_in_outcome_{istm} = \sum_{\tau=2011 \tau \neq 2013}^{2016} \beta_\tau \mathbb{1}\{t = \tau\} \cdot positive_gain_{ism} + \\ + \beta_{pg} \cdot positive_gain_{ism} + \delta_t + \delta_s + \delta_{gpa_decile} + \varepsilon_{istm}, \tag{5}$$

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 predetermined controls as in analysis following equation 4. 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.

5. RESULTS

5.1. 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 (4). 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 F reports analogous results using a restricted sample of students who, in twelfth grade, lived in the same county as during primary school and Appendix E presents results using alternative treatment measures.

Consistent with strategic behavior, students with a positive gain in their educational market are 1.2 pp likelier to switch schools during twelfth grade (p-value = 0.00) relative to the year before the RR policy formula was made public. This effect represents an increase of 63% relative to the sample mean (0.019) in the prepolicy 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 1, 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 1.3 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 pp (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 heterogeneous effects confirms that impacts differ 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 likelier 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 (4) on a month-by-month basis rather than yearly. The figure shows that students with a positive potential gain are likelier to switch schools toward the end of the academic year, providing further support for the interpretation that these transfers reflect strategic behavior.

I also perform the same analysis focusing on school relocation that occur at the beginning of the academic year, with results presented in Figure A6. If the observed 2014 differential switching were instead driven by non-strategic confounders, then we would also expect elevated switching at conventional times like 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 and medium-SES students attending high-performing public schools whose parents had high educational aspirations for them before the policy change.

Figures 10 and 9 plot the interaction coefficients between having a positive potential gain and event-year dummies, estimated using Equation 4, in samples divided according to different dimensions of heterogeneity. Figure 10, 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 pp 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 pp 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 supports 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 9 presents the coefficients from Equation 4, estimated separately by SES (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 pp 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 home internet access, respectively. Gender differences are small and statistically insignificant, suggesting that male and female students responded similarly to the policy's information release. Students with internet access at home are more likely to switch schools than those without access, although this difference is statistically significant only at the 5 percent 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 (4) 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 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

[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.

performance. Figure 12 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 2014-year dummy—the coefficient of interest—for Chile (left) and Santiago (right). Figures A8-A14 display the corresponding event-study estimates for each outcome separately.

In the national sample (Panel A), students with a positive potential gain are about 1 pp likelier 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 pp likelier to switch to schools with lower RR thresholds and lower post-graduation academic performance. They are also likelier 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.

5.2. 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 (5). 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 likelier 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 13 plots the coefficients on the interaction between the positive potential gain indicator and event-year dummies for students living in Santiago (the sample covers cohorts graduating

between 2011 and 2016; see Section 3.3 for details on this restriction). 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 pp likelier to be admitted to a highly selective program (p-value=0.081) and 1.4 pp likelier to enroll in such a program (p-value=0.038) in 2014, the year following the public release of the RR policy formula. Figure A15 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).

I also examine whether the policy disclosure affected students' application behavior. Students with a positive potential gain are 0.9 pp more likely to apply to highly selective programs (p-value < 0.05) and 1.2 pp more likely to apply to elite universities following the disclosure (Figure A16). These effects indicate that students who stood to benefit from switching also applied somewhat more ambitiously, consistent with the score boost expanding the set of programs for which they were competitive.

Next, I examine college outcomes in the long-run. To do so, I estimate Equation (4) 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 11 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, students with a positive potential gain are 2.6 pp 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 A16 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 pp likelier to switch schools during twelfth grade. The magnitude of the 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. I also find that they are approximately 1 p.p. more likely to apply to highly selective programs.

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 pp and 55 pp, respectively.

6. 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% 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% due to the equilibrium effects of school switching.

6.1. 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 making it harder to use any type of difference-in-difference event study design (see Figure A7 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 prepolicy weights from the 2012 admission cycle, which serve as the baseline for evaluating changes in the composition of admitted students.

One limitation of this exercise is that application portfolios are held constant across scenarios. In practice, students with positive gains also apply somewhat more ambitiously following the disclosure (see Section 5.2). Because the simulation does not adjust these portfolios in the no-switching counterfactual, it understates how many selective seats would be opened for low-SES students in the absences of the strategic behavior, making the estimated effect conservative.

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:

$$(6) \quad \Delta^{Benchmark}_{g,2015,d} = 100 * \left(\frac{\#\text{ students accepted with no students switched schools}_{g,2015,d}}{\#\text{ students accepted using 2012 weights}_{g,2015,d}} - 1\right),$$

and

$$(7) \quad \Delta^{Switches}_{g,2015,d} = 100 * \left(\frac{\#\text{ students accepted with students relocation}_{g,2015,d}}{\#\text{students accepted using 2012 weights}_{g,2015,d}} - 1\right),$$

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.

6.2. 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 1.3). Figure 14 reports simulated distributional effects by SES, 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 rates at *Tier 1* universities, the policy's intended effect is substantially attenuated by strategic behavior. Absent switching, the RR policy would have increased low-SES acceptance rates at Tier 1 universities by 5.0%; with switching, this effect falls to 3.5%—a reduction of approximately 30%.

Figures A17 and A18 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).

6.3. 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, policies that tie eligibility to the school a student graduates from can create incentives to game the system—and the severity of these incentives depends critically on specific design features. Three institutional characteristics made Chile's RR policy particularly vulnerable to strategic manipulation. First, GPAs are portable across schools: a student's cumulative GPA travels with them when they transfer, so relocating does not require rebuilding an academic record. Second, the relative ranking was calculated solely at the school from which the student graduated, creating a direct reward for last-minute transfers. Third, Chile's open enrollment system imposes no penalties or waiting periods for school switches, allowing students to transfer mid-year during twelfth grade at minimal cost. The combination of these features—portable grades, graduation-school-only ranking, and frictionless transfers—generated a setting where strategic behavior was both feasible and profitable. The comparison with Texas' Top Ten Percent plan illustrates how design features govern the magnitude of strategic responses. Under that policy, school administrators typically require transferring students to attend for some period before qualifying for top 10% placement, and families must commit to a less competitive high school years in advance—at the 8th-to-10th grade transition. These frictions substantially raise the cost of strategizing, and Cullen, Long, and Reback (2013) find a correspondingly smaller response: 211 students per cohort statewide, displacing 12 minority students per year from the top 10% pool. In Chile, where students could transfer mid-year during their final year at no cost, the behavioral response is more than twice as large and displaces roughly 27 low-SES students per cohort from Tier 1 universities—about 1 in 18 disadvantaged students who would otherwise have been admitted. These results suggest that the key design margin is not whether a policy uses school-specific relative performance, but how costly it is for students to change their reference group.

Figure A19 illustrates the consequences of ignoring these strategic responses when evaluating policy effectiveness. Strategic 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 prepolicy school affiliation tend to overstate the policy's effects by 100%, as they do not account for changes in school composition.

7. 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 likelier 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.

FIGURES AND TABLES

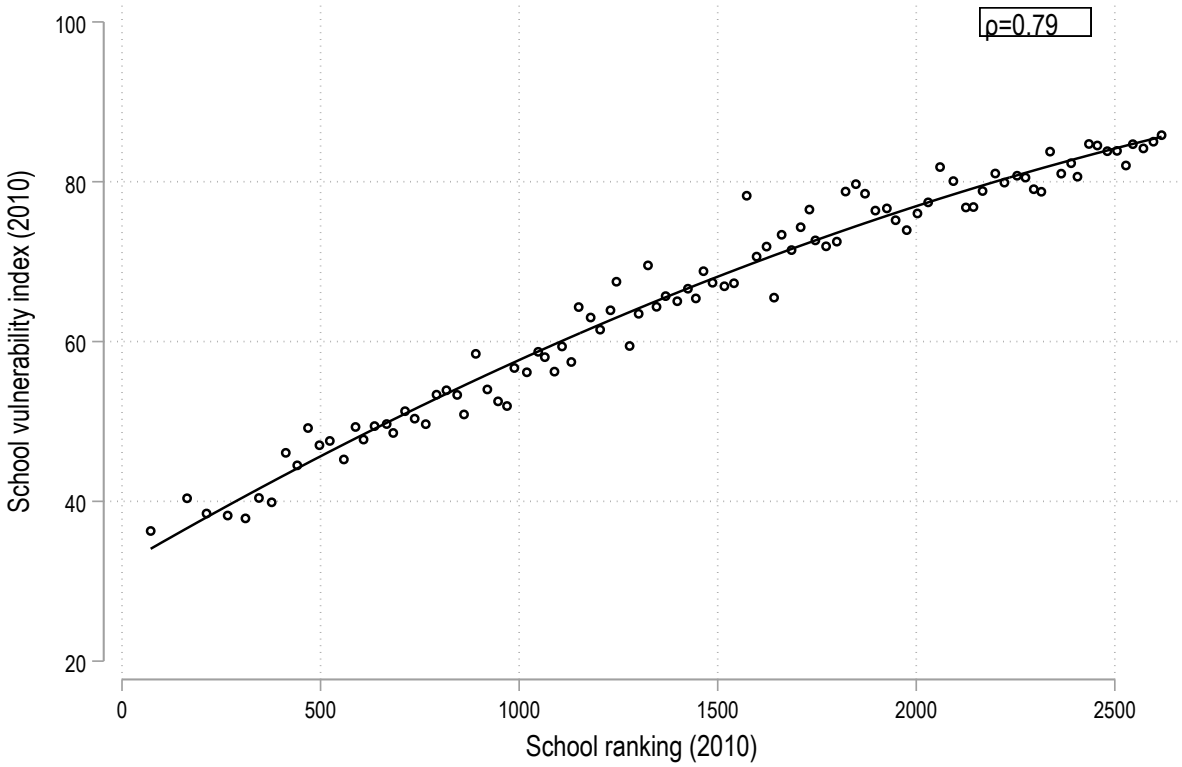


FIGURE 1. School Vulnerability Index & School Ranking

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.

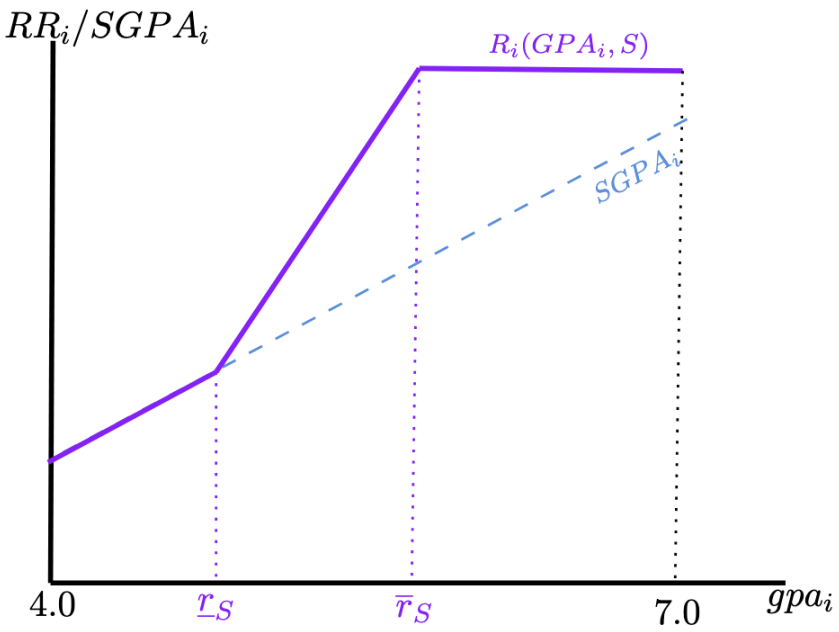


FIGURE 2. Relative Ranking Component Visualization

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.

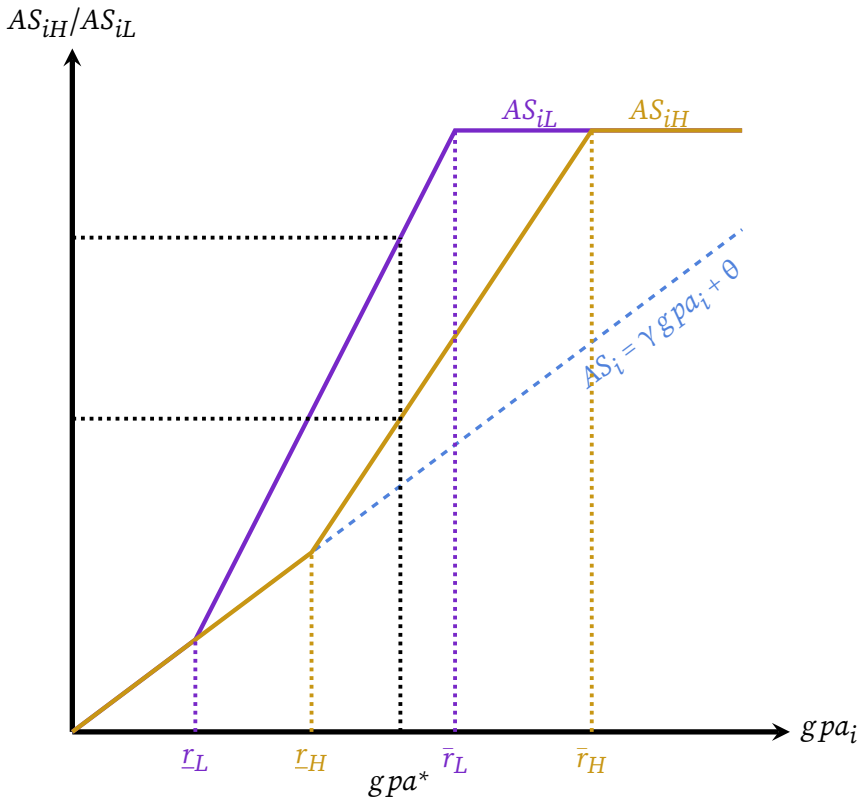


FIGURE 3. Same Thresholds' Order

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. $\bar{r}_L$ and $\bar{r}_H$ represent the maximum threshold, which is equal to the best student from the three previous cohorts' GPA.

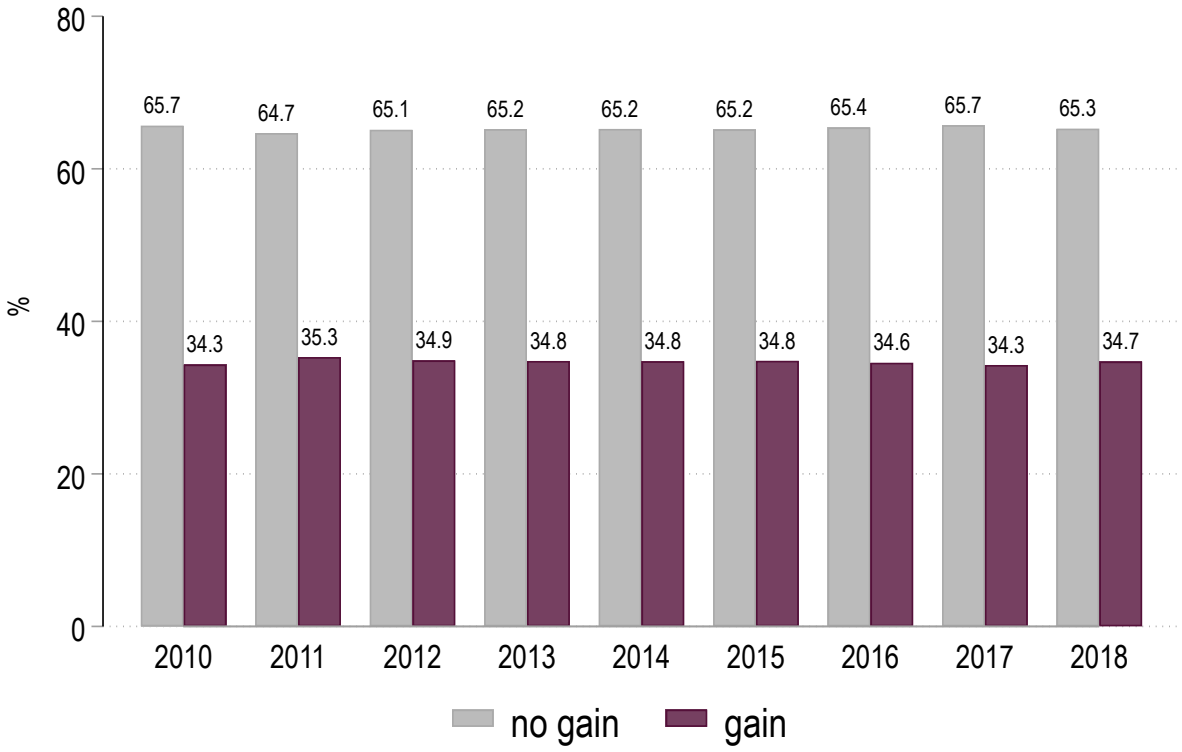
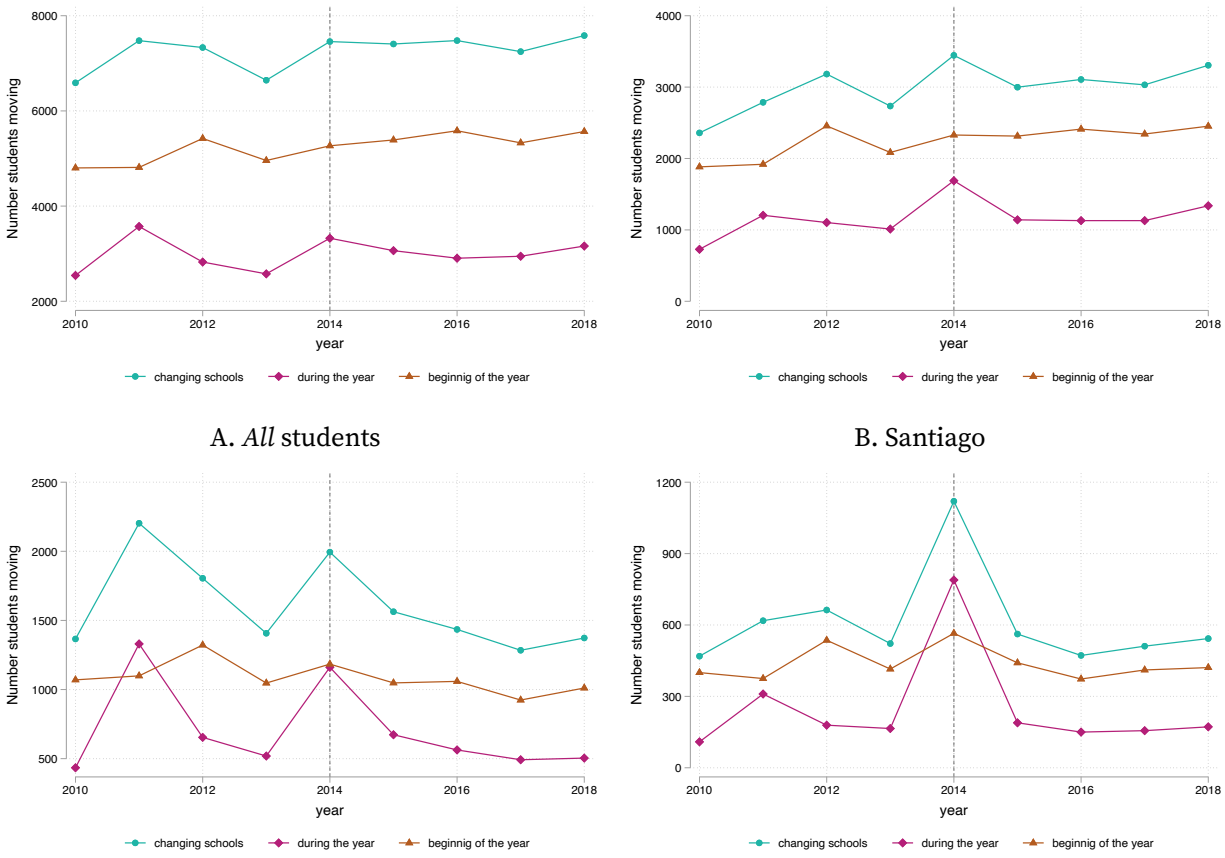


FIGURE 4. Ratio Students with Positive Potential Gain.

Note: This figure presents the percentage 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.



A. *All* students

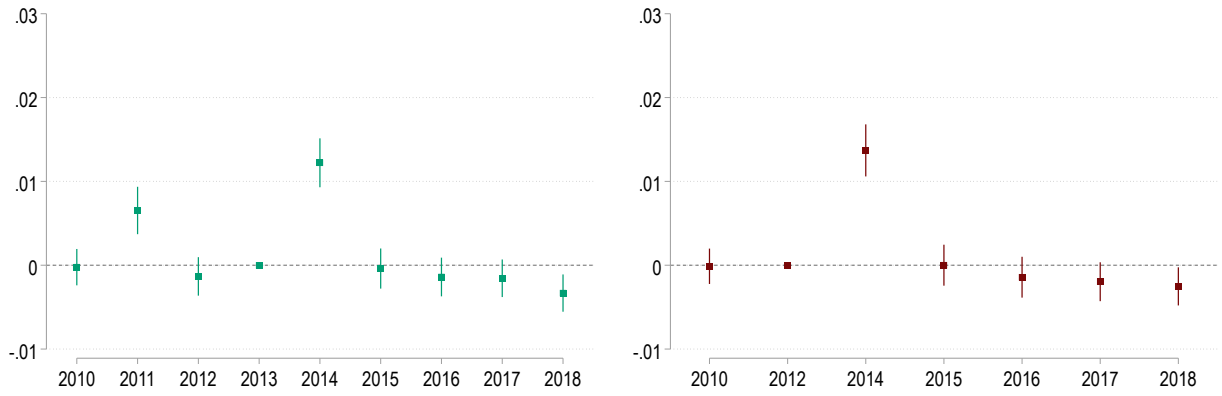
B. Santiago

C. *High-Performing* Schools

D. *High-Performing* Schools in Santiago

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

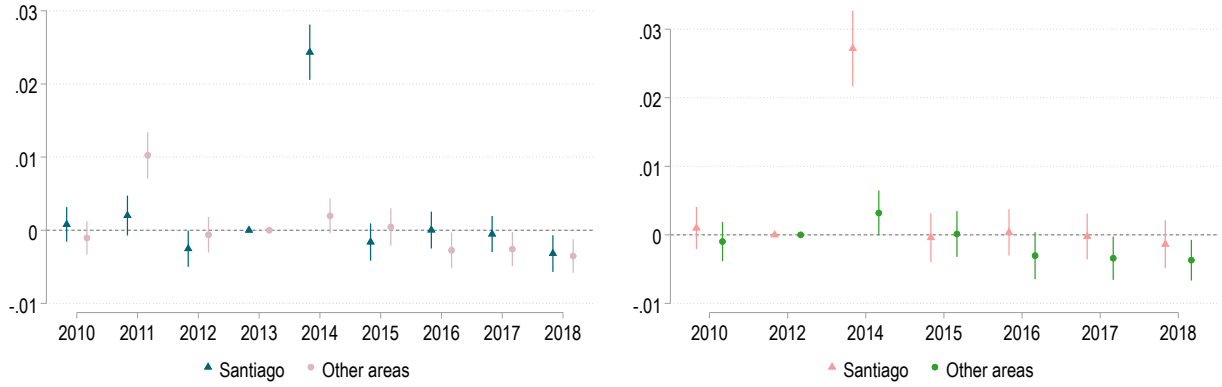
Note: This figure reports the total number of students switching schools in 12th grade by year. In each panel, circles indicate the total number of students switching schools in that year, triangles represent switches occurring at the beginning of 12th grade, and diamonds represent switches taking place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



A. Within-School GPA Controls B. Standardized Test Controls

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

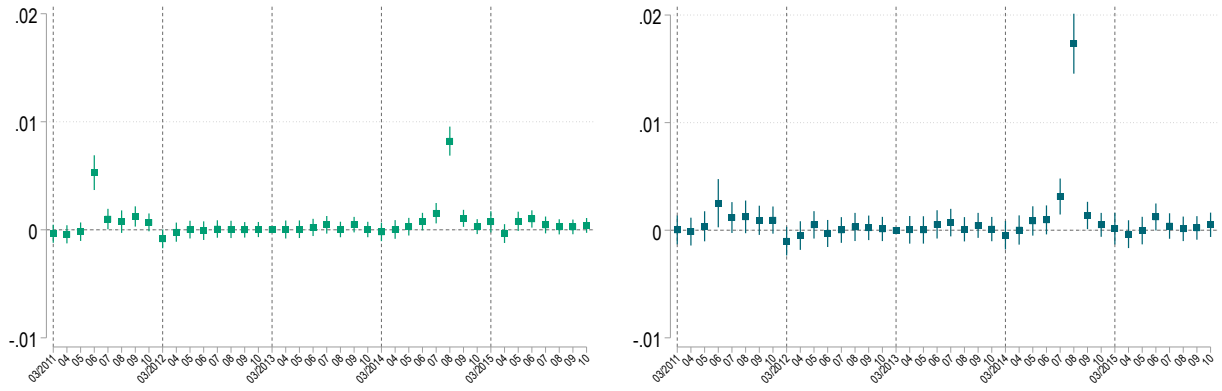
Note: This figure plots the coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive potential gain and event-year dummies. Panel A includes fixed effects for within-school 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.



A. Within-school GPA Controls B. Standardized Test Controls

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

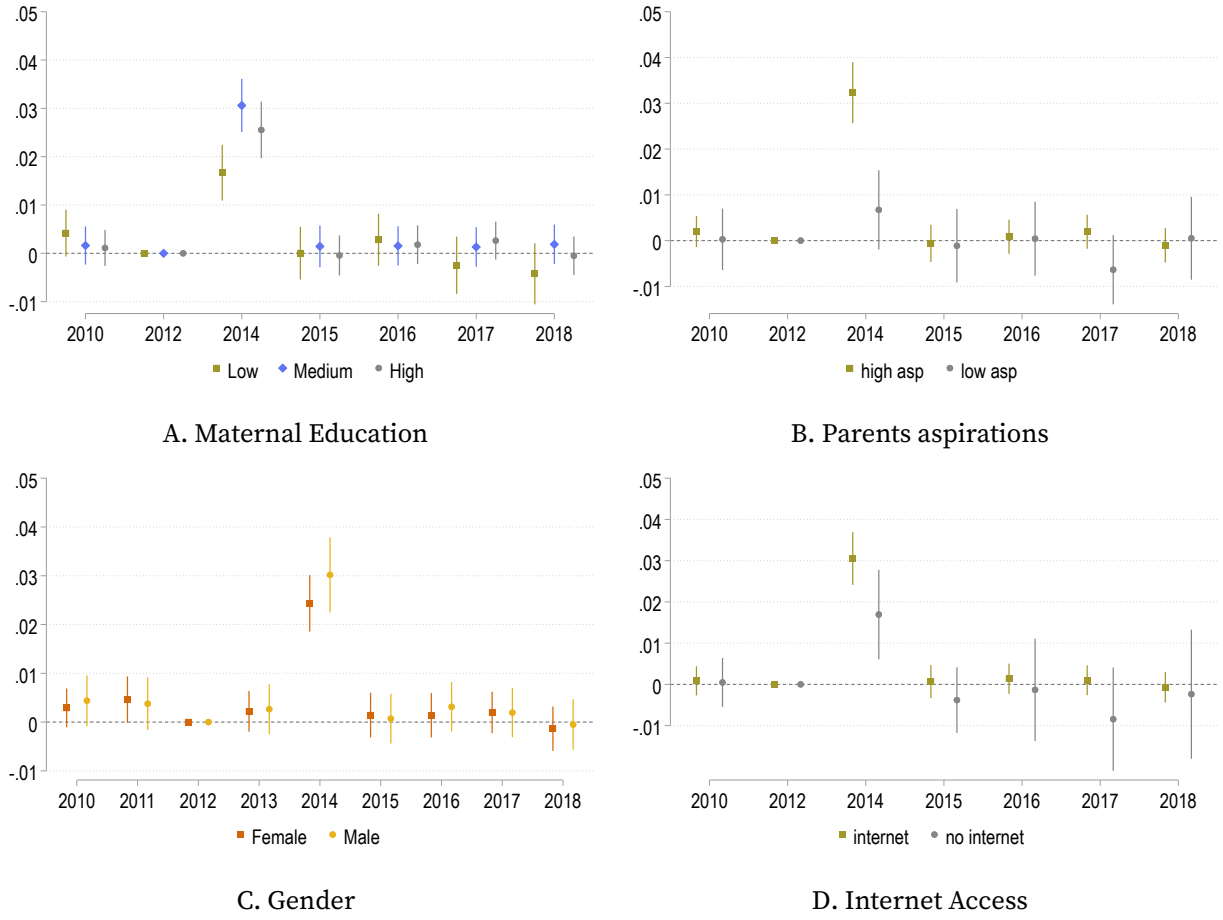
Note: This figure plots the coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between having a positive gain and event-year dummies, estimated separately for two samples: students living in Santiago (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.



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 (4), 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.



A. Maternal Education

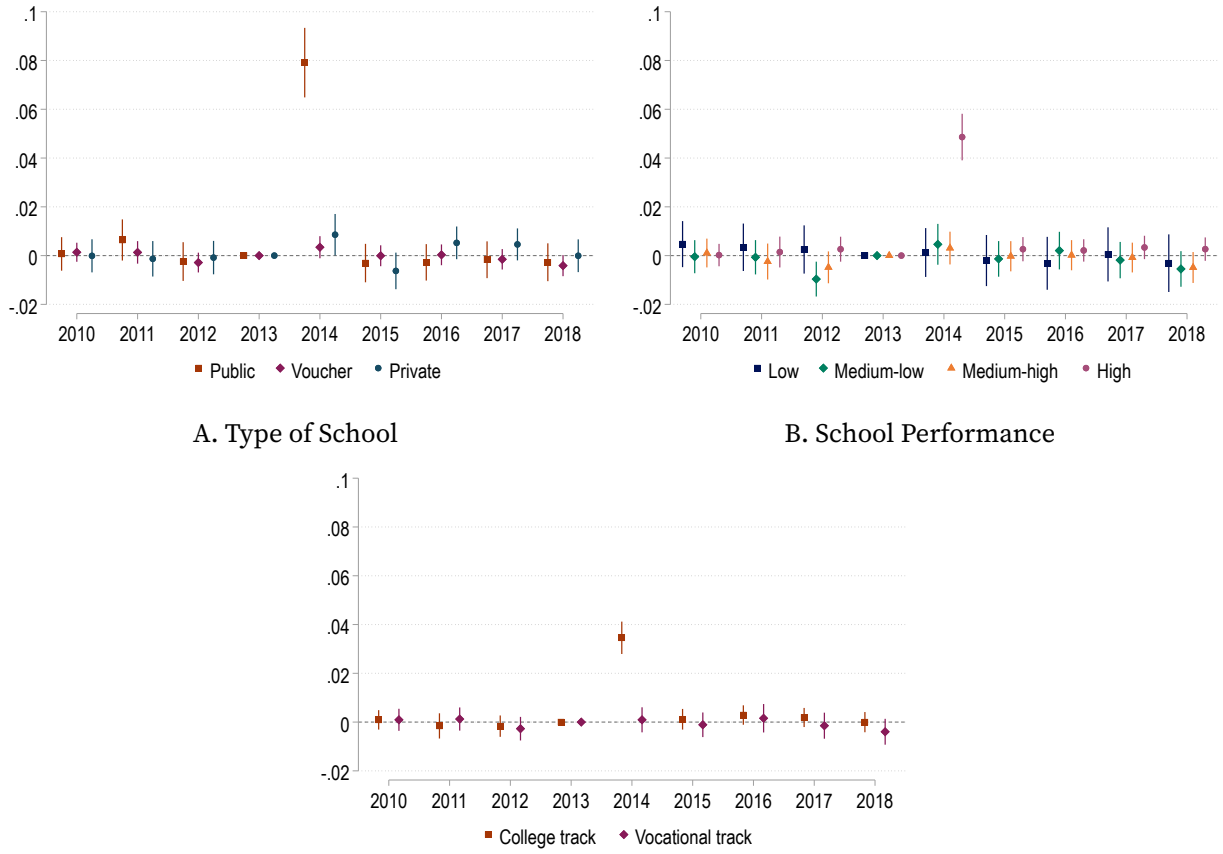
B. Parents aspirations

C. Gender

D. Internet Access

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

Note: This figure plots the coefficients from estimating equation (4) 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 maternal education, 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.



A. Type of School

B. School Performance

C. School Track

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

Note: This figure plots the coefficients from estimating equation (4) 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 school-performance in the 10th grade standardized test, and Panel C presents the results by school track. 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.

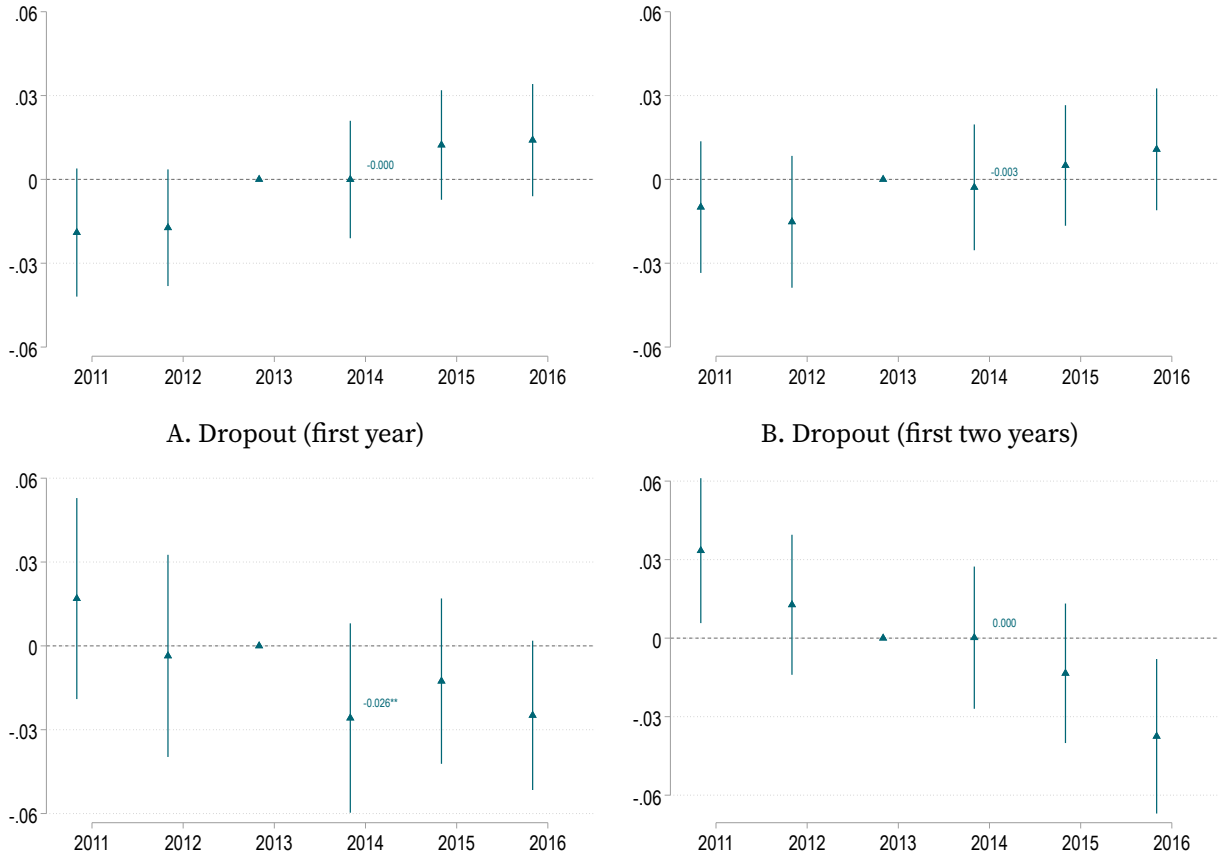
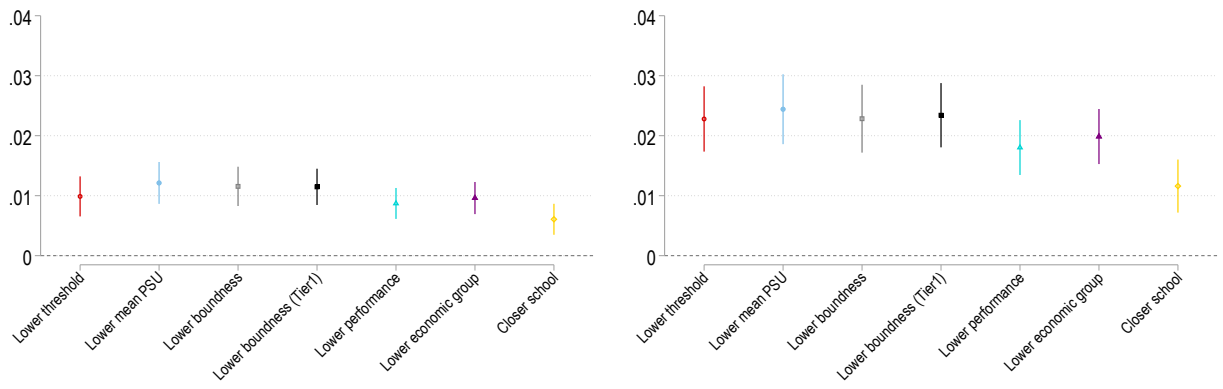


FIGURE 11. Impact of the RR Policy Disclosure on Dropout and Graduation Outcomes

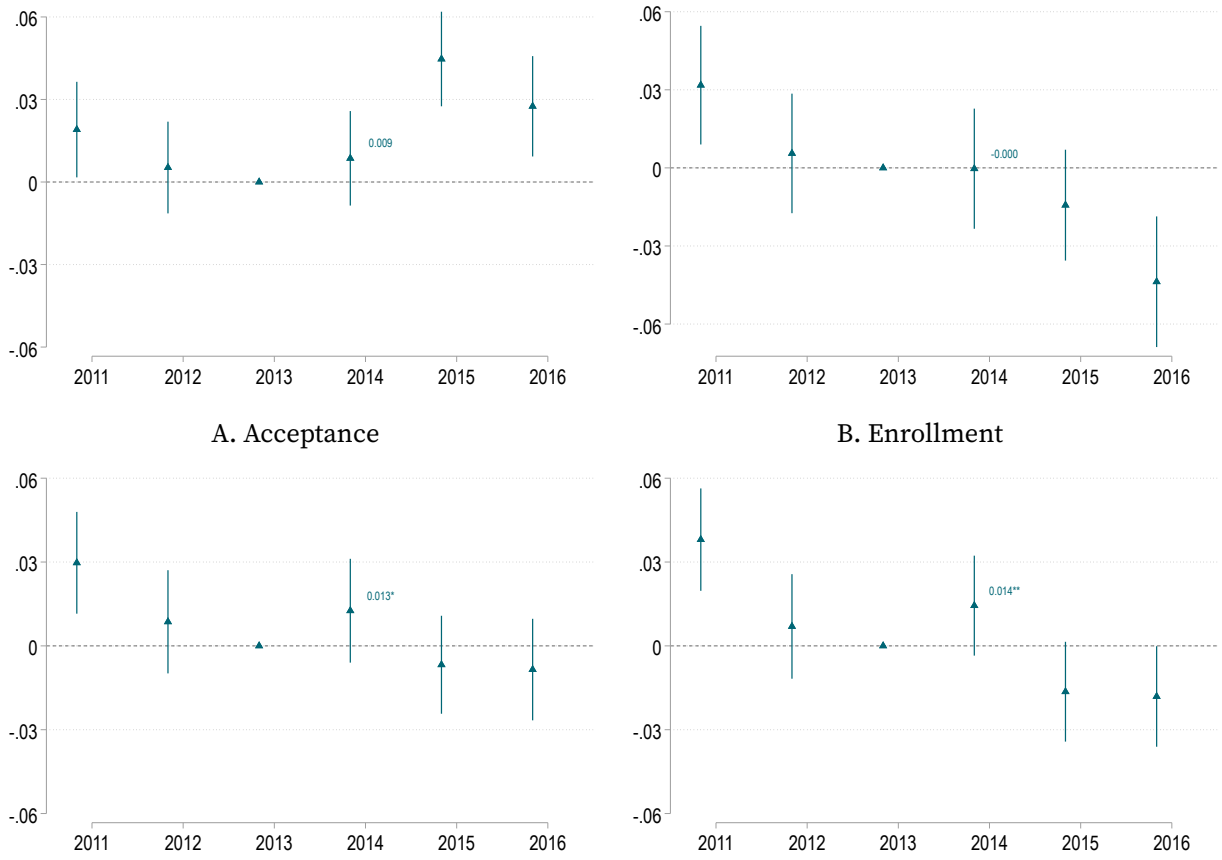
Note: This figure plots the coefficients from estimating equation (4) in the sample of students living in Santiago, where the outcome is an indicator for dropping out during the first year student enrolled in a university (Panel A), dropping out during the first two years (Panel B), graduating on time (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% (*).



A. Chile B. Santiago

FIGURE 12. 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 (4) 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.



A. Acceptance

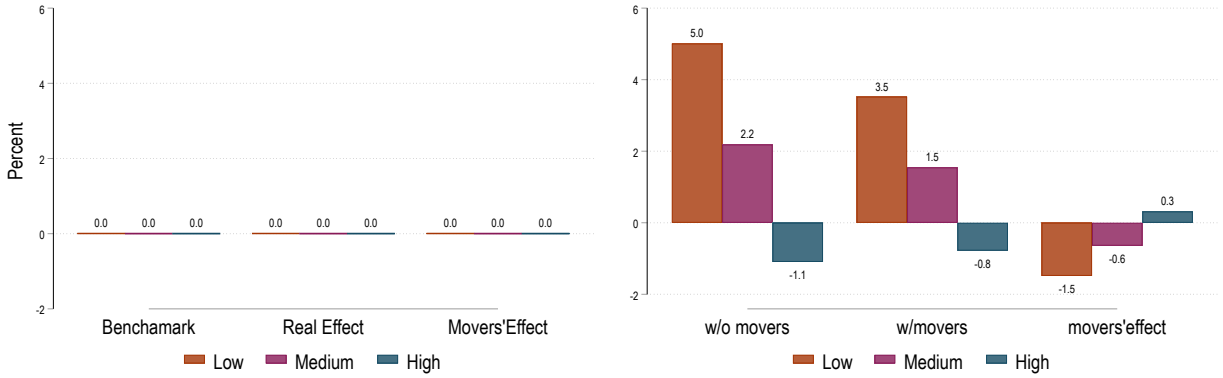
B. Enrollment

C. Acceptance in High Selective Programs

D. Enrollment in High Selective Programs

FIGURE 13. Impact of the RR Policy Disclosure on University Admission and Enrollment

Note: This figure plots the coefficients from estimating equation (4) 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% (*).



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 (6) and Equation (7) 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 students were not allowed to switch schools relatively to the prepolicy acceptance rates, the next three columns the change in the acceptance rate when students switched relative to the prepolicy 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 college for the AY 2015.

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.

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 in 12th grade (beginning or during the AY)	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 private 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
Attending Q1 schools	0.16	0.36	0.20	0.40	0.09	0.28
Attending Q2 schools	0.24	0.42	0.27	0.45	0.17	0.38
Attending Q3 schools	0.26	0.44	0.26	0.44	0.25	0.43
Attending 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.

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	0.26	0.44	0.17	0.37	0.34	0.47
Accepted in a university	0.79	0.40	0.71	0.45	0.86	0.34
Accepted in an elite university	0.11	0.31	0.06	0.23	0.15	0.36
Enrolled in a university	0.72	0.45	0.64	0.48	0.79	0.41
Enrolled in an elite university	0.11	0.31	0.06	0.23	0.15	0.35
Graduated at all	0.28	0.45	0.21	0.41	0.33	0.47
Graduated graduated on time	0.22	0.41	0.16	0.37	0.26	0.44
Panel B: *Characteristics (Used as Controls in decile bins)*						
GPA (non-standardized)	5.89	0.47	5.68	0.49	6.05	0.38
10th grade standardized score	0.82	0.80	0.58	0.81	1.02	0.72
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	0.22	0.42	0.22	0.42	0.22	0.42
Attending voucher schools	0.54	0.50	0.58	0.49	0.51	0.50
Attending private schools	0.23	0.42	0.19	0.40	0.27	0.44
Attending national test prep. track	0.83	0.38	0.76	0.42	0.88	0.32
Attending vocational track	0.13	0.34	0.18	0.38	0.09	0.29
Atending Q1 schools	0.06	0.24	0.09	0.29	0.03	0.17
Atending Q2 schools	0.15	0.36	0.20	0.40	0.12	0.32
Atending Q3 schools	0.26	0.44	0.28	0.45	0.24	0.43
Atending Q4 schools	0.53	0.50	0.43	0.49	0.61	0.49
Mother education < HS	0.16	0.36	0.18	0.39	0.14	0.34
Mother education = HS	0.44	0.50	0.46	0.50	0.43	0.50
Mother education > HS	0.40	0.49	0.36	0.48	0.43	0.50
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	0.08	0.28	0.12	0.33	0.05	0.23
High aspirations	0.92	0.28	0.88	0.33	0.95	0.23
Does not have access to internet	0.14	0.34	0.16	0.36	0.12	0.33
Has access to internet	0.86	0.34	0.84	0.36	0.88	0.33
Switch school during the year	0.01	0.11	0.01	0.11	0.01	0.11
Observations	287,828		126,494		161,334	

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.

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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.

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

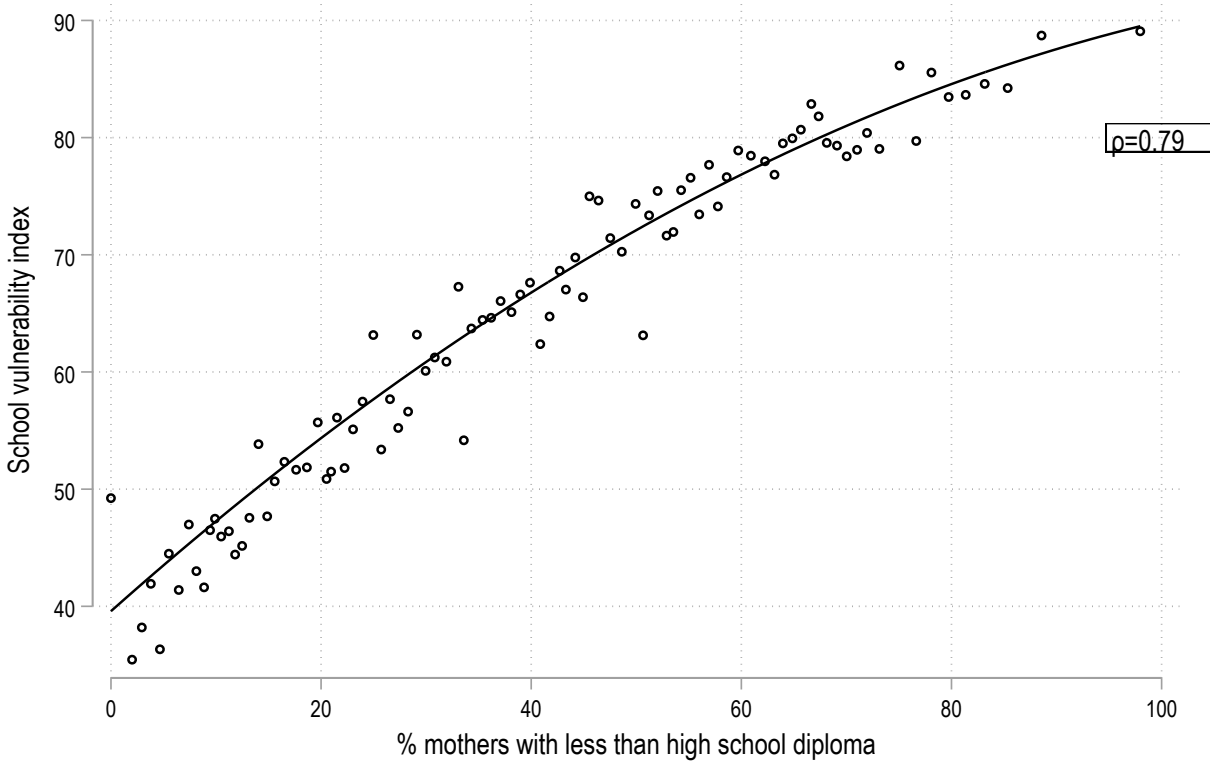


FIGURE A1. School vulnerability index & students SES

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

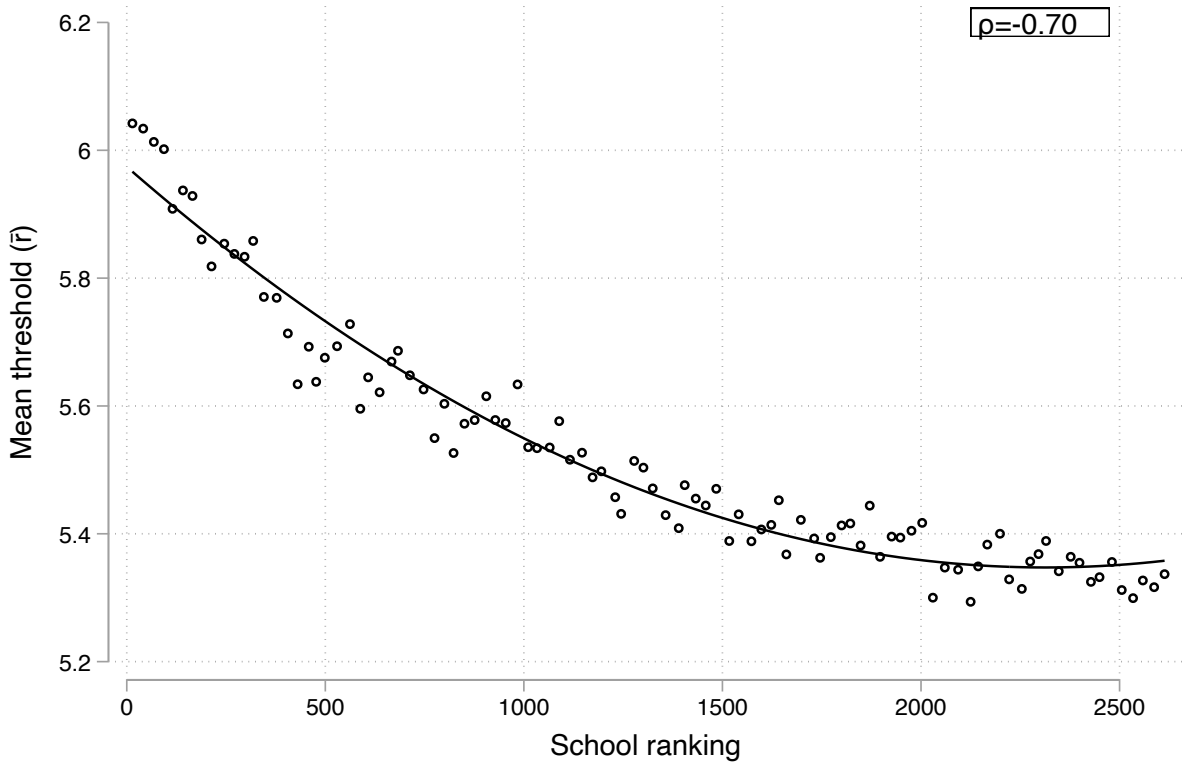
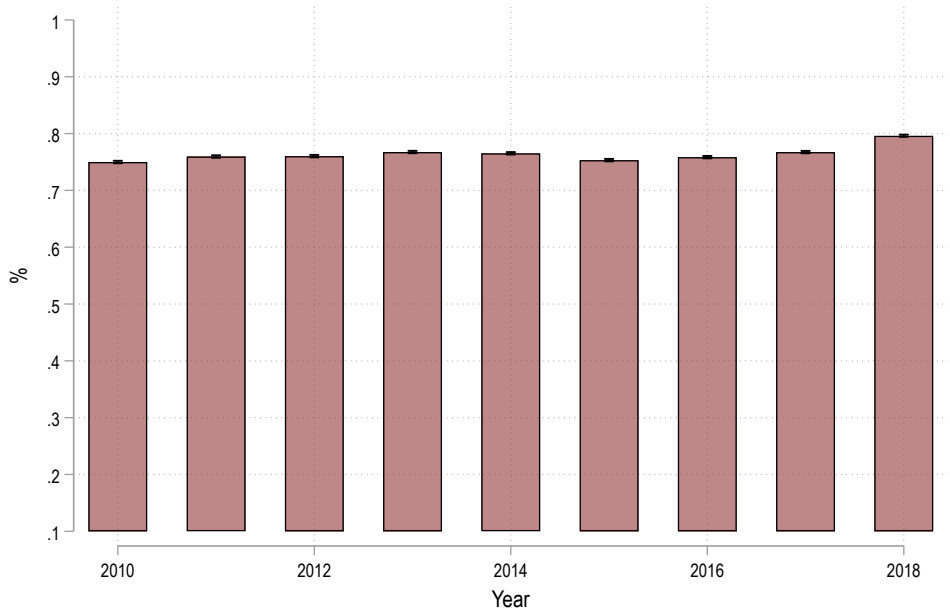
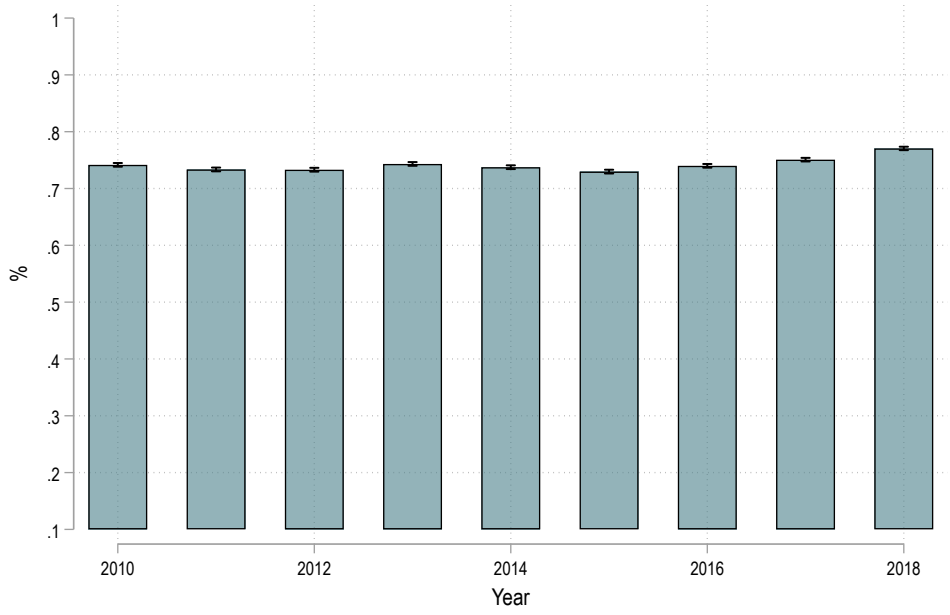


FIGURE A3. School Mean Threshold & School Ranking

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 school mean threshold measured as the average GPA from the three previous cohorts (y-axis) between 2010-2013.



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.

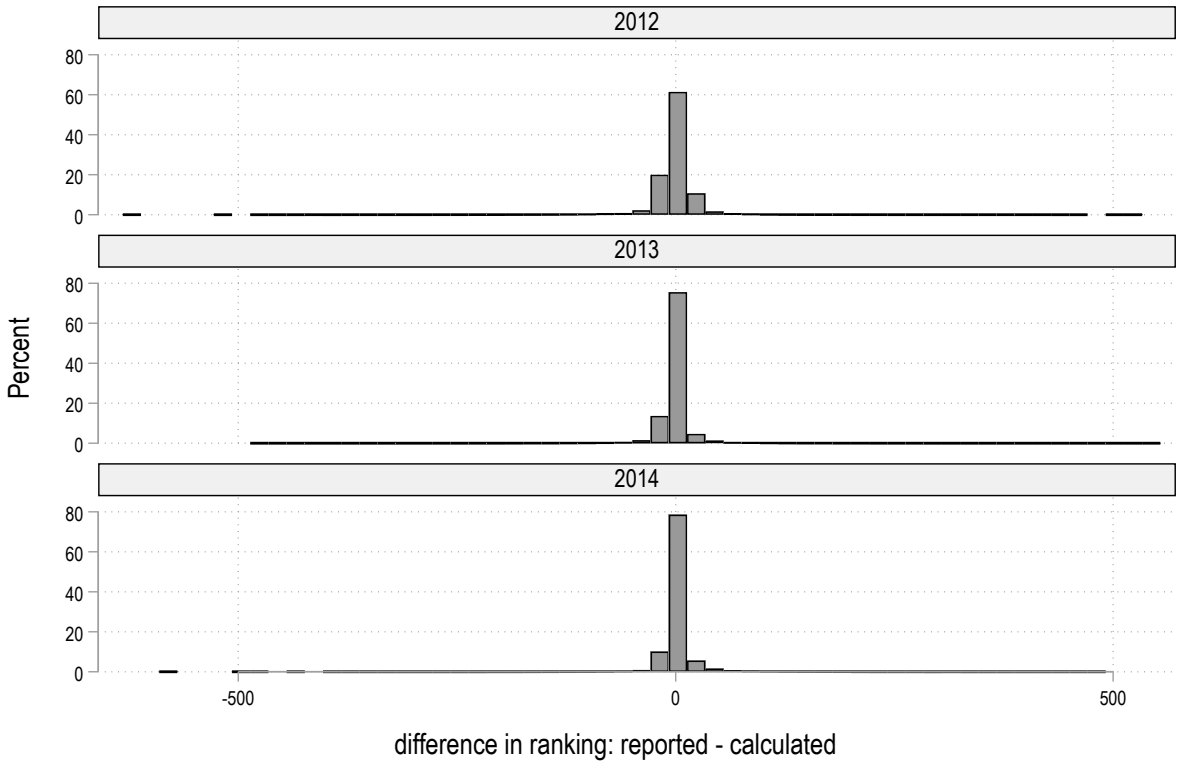


FIGURE A4. Difference between Reported Ranking Score and Calculated Ranking Score.

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

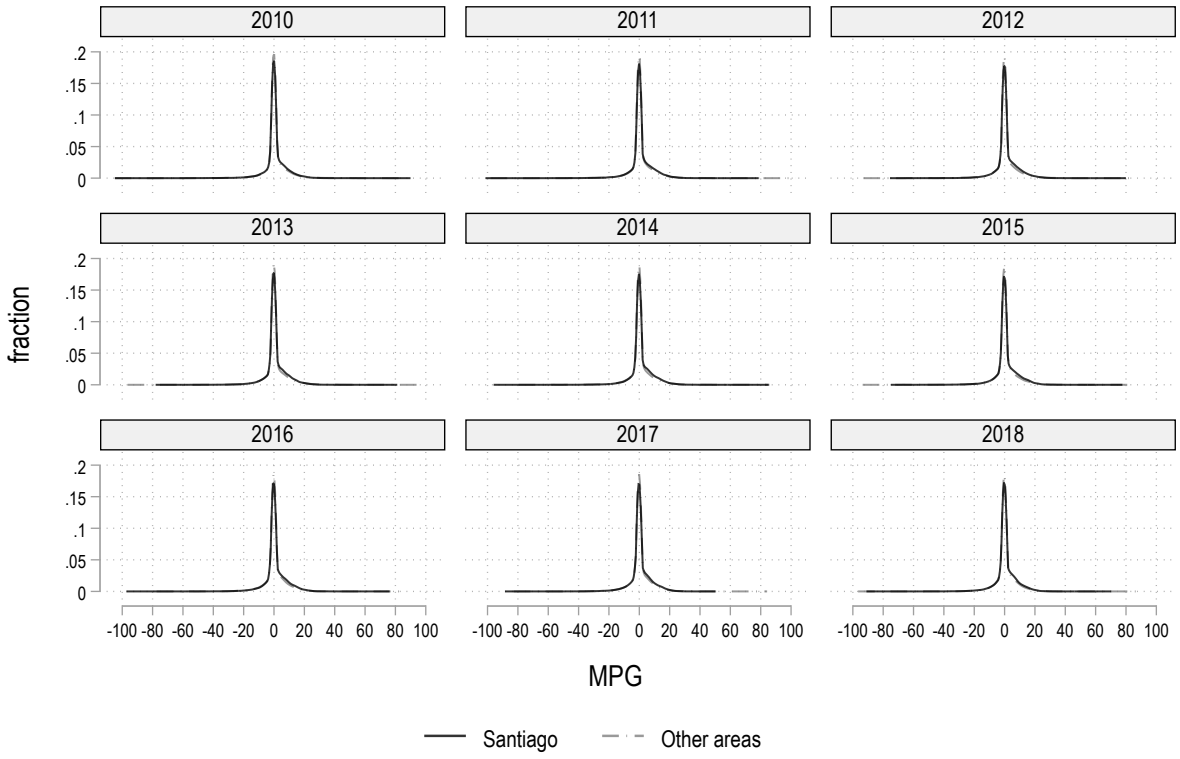
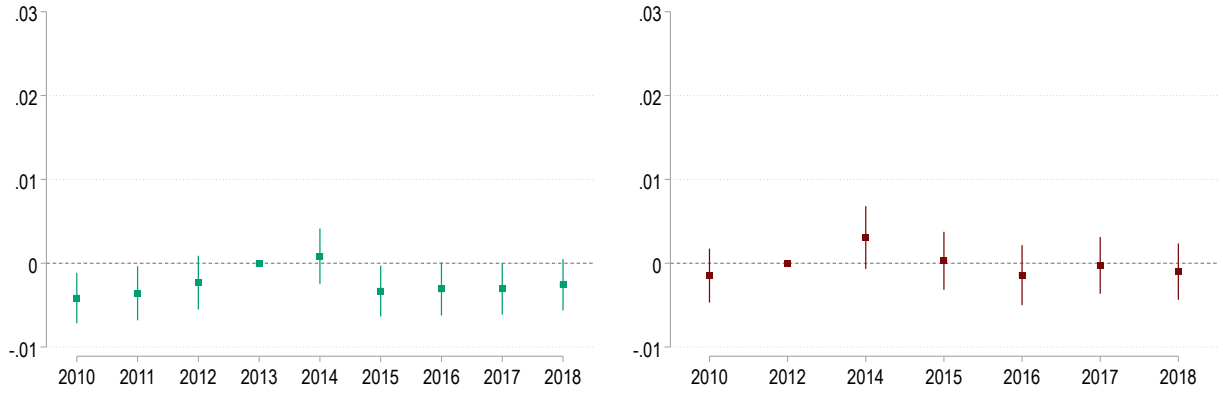


FIGURE A5. Median Potential Gain's Distribution by Year and Area.

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 A6. 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 (4), 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.

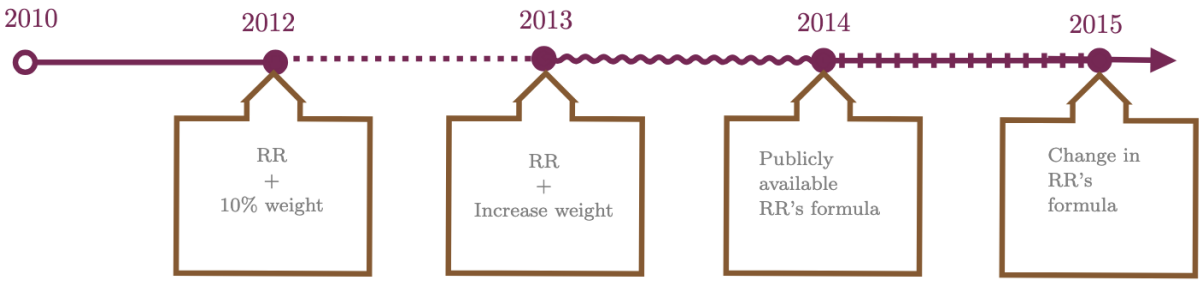
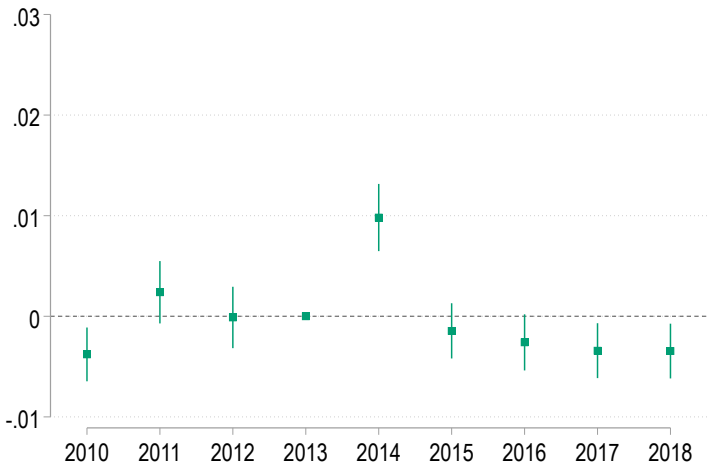
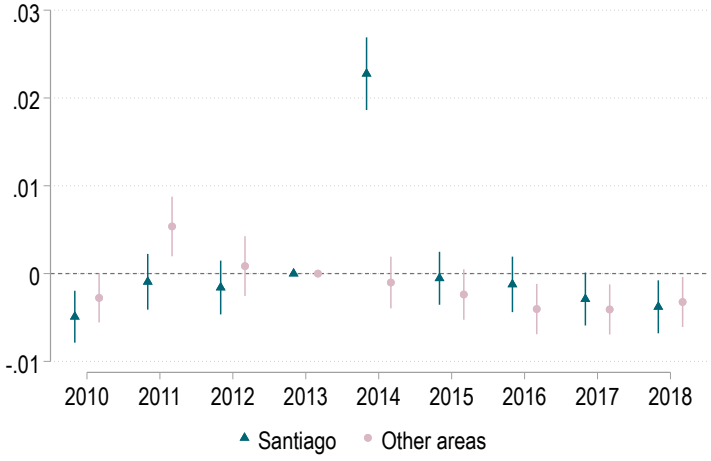


FIGURE A7. Relative ranking policy's timeline

Notes: This timeline presents the changes made to the RR policy in different years. In 2012 they incorporated the policy with a weight of 10%. 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.



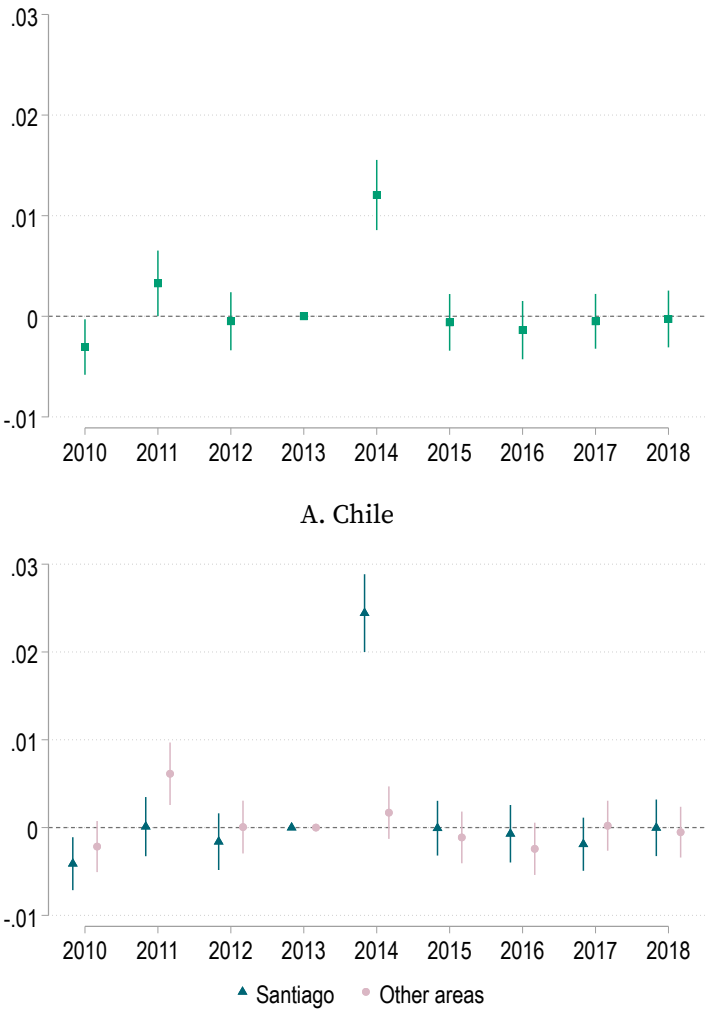
A. Chile



B. Santiago

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

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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.

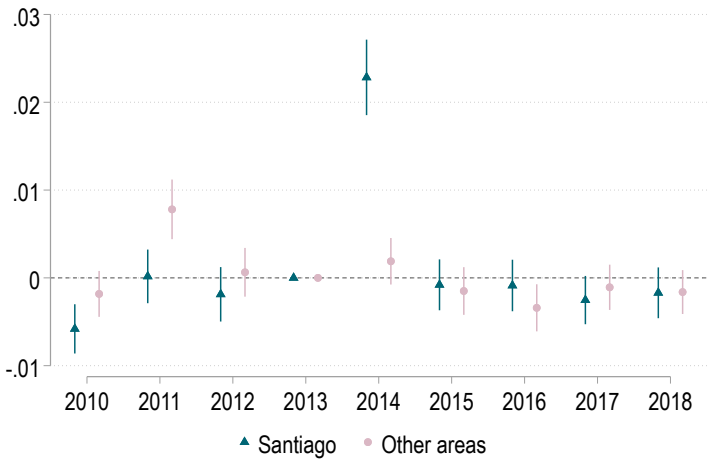


A. Chile

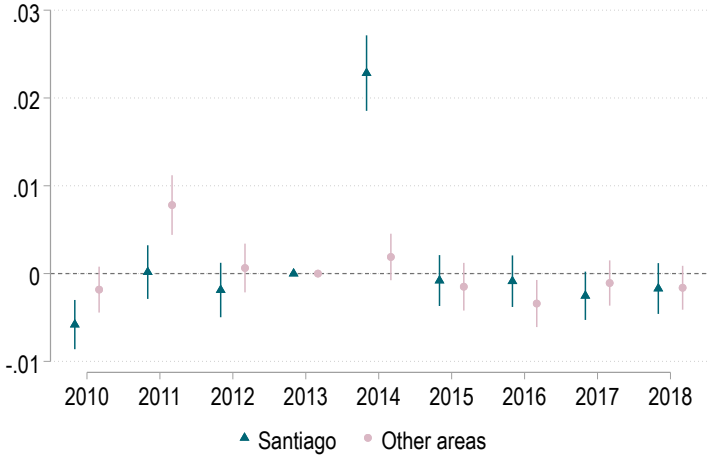
B. Santiago

FIGURE A9. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower National Test Score Schools

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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.



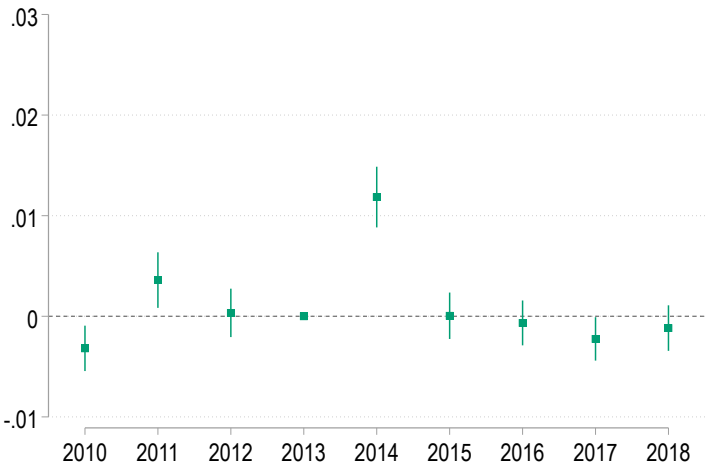
A. Chile



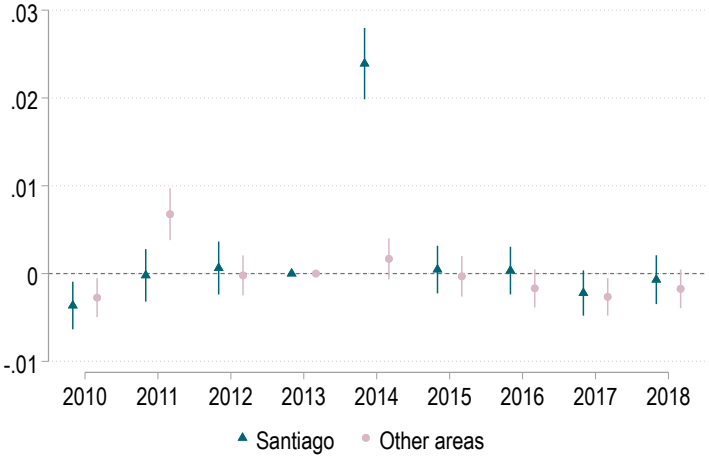
B. Santiago

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

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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.



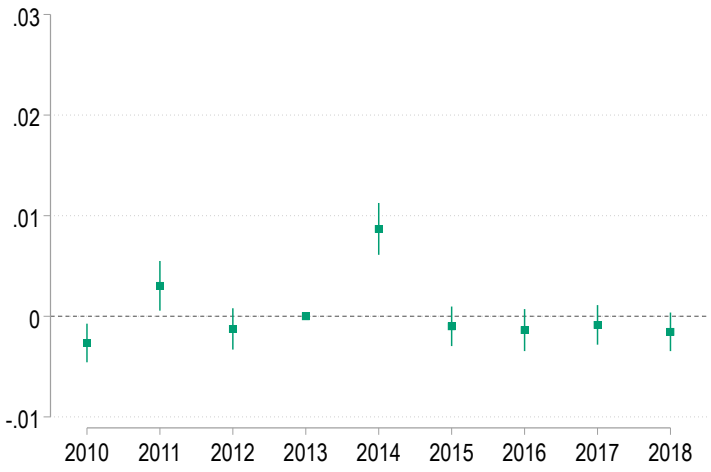
A. Chile



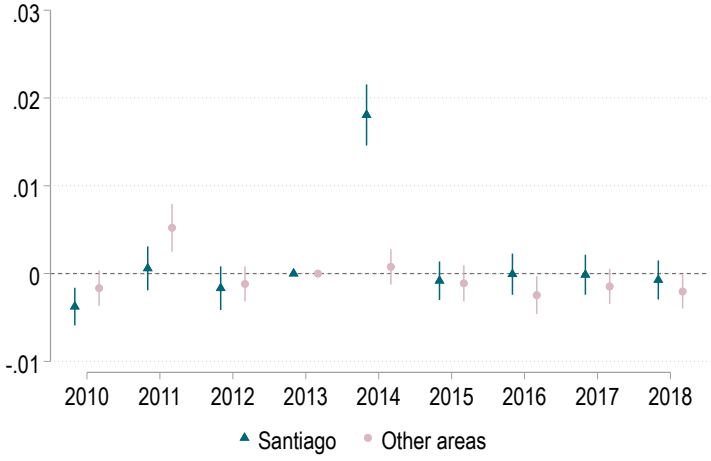
B. Santiago

FIGURE A11. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower Tier-One-College-Sending Schools

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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.



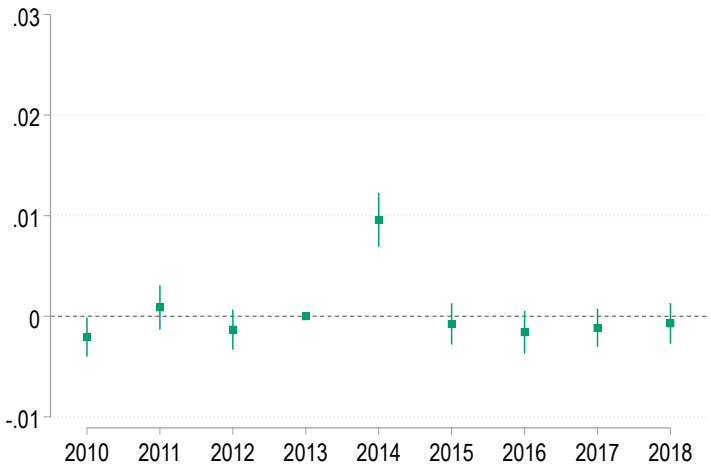
A. Chile



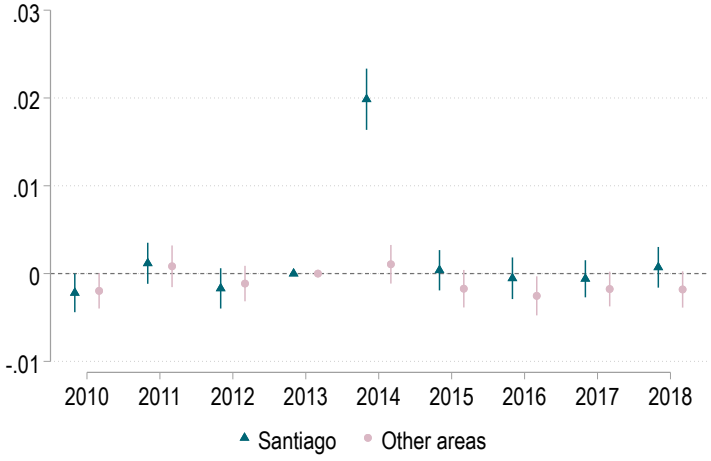
B. Santiago

FIGURE A12. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Lower Performing Schools

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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.



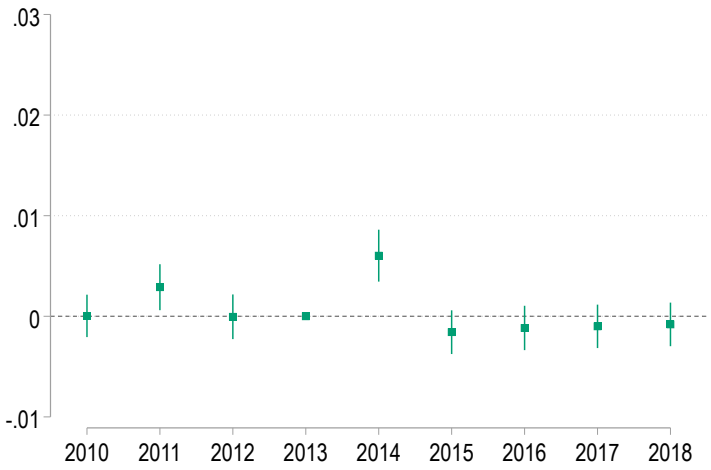
A. Chile



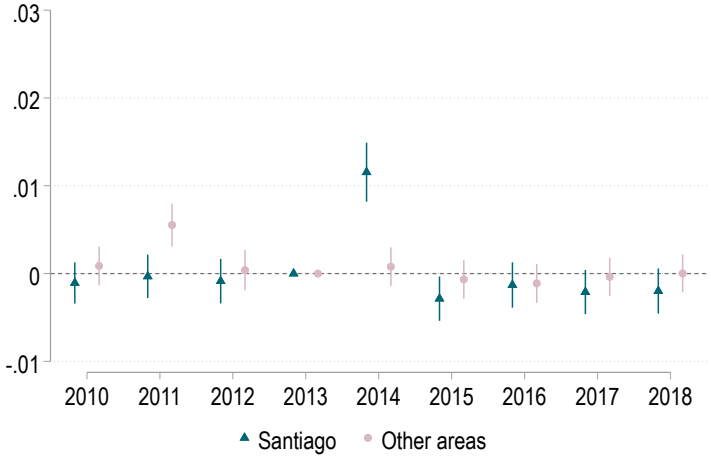
B. Santiago

FIGURE A13. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Schools with More Disadvataged Students

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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.



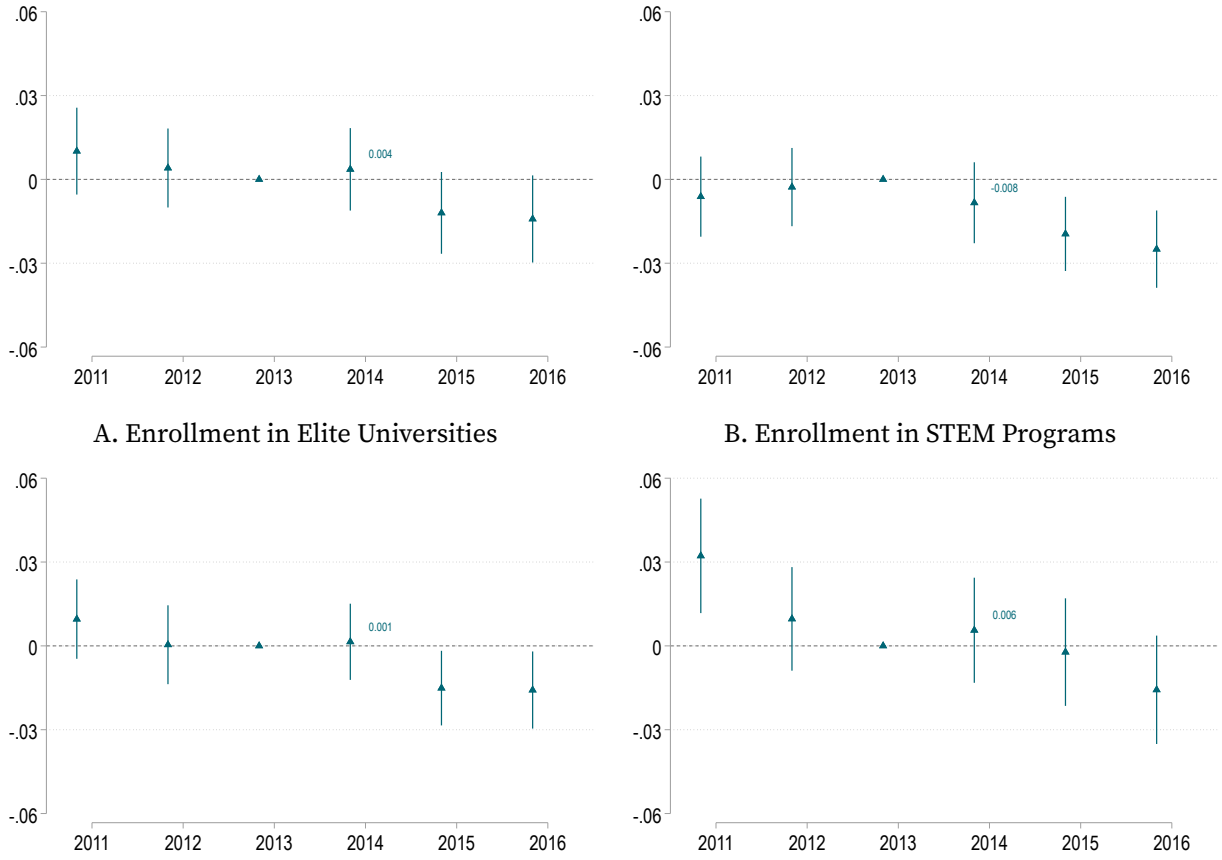
A. Chile



B. Santiago

FIGURE A14. Impact of the RR Policy Disclosure on Students' School Switching: Targeting Schools Closer to Home

Note: This figure plots the coefficients from estimating equation (4), 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 (4) 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

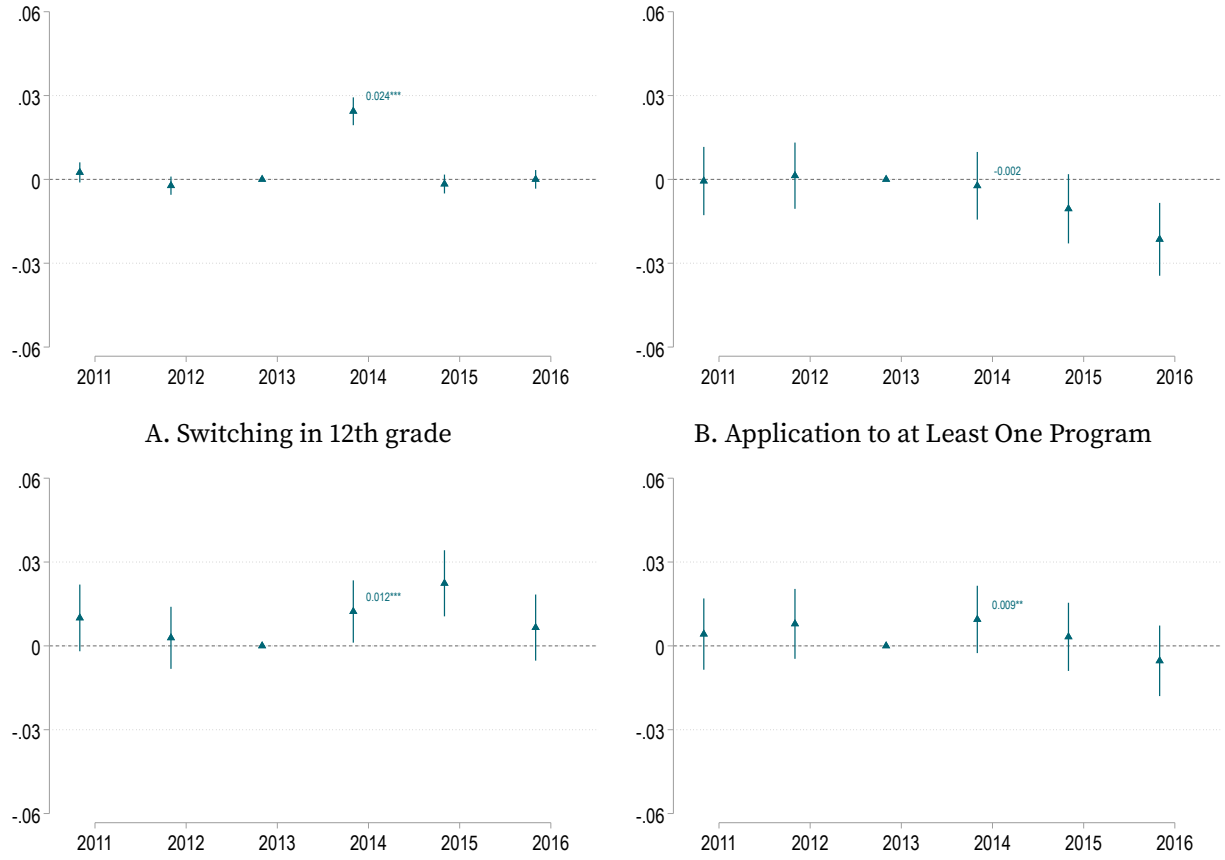
B. Enrollment in STEM Programs

C. Enrollment in *Traditional* Programs

D. Enrollment in High Return Programs

FIGURE A15. Impact of the RR Policy Disclosure on University Admission and Enrollment

Note: This figure plots the coefficients from estimating equation (4) 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

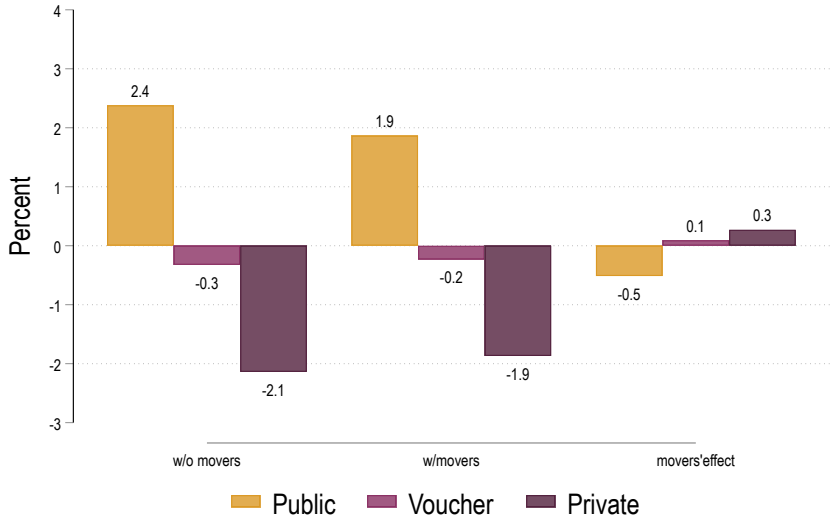
B. Application to at Least One Program

C. Application: Elite University

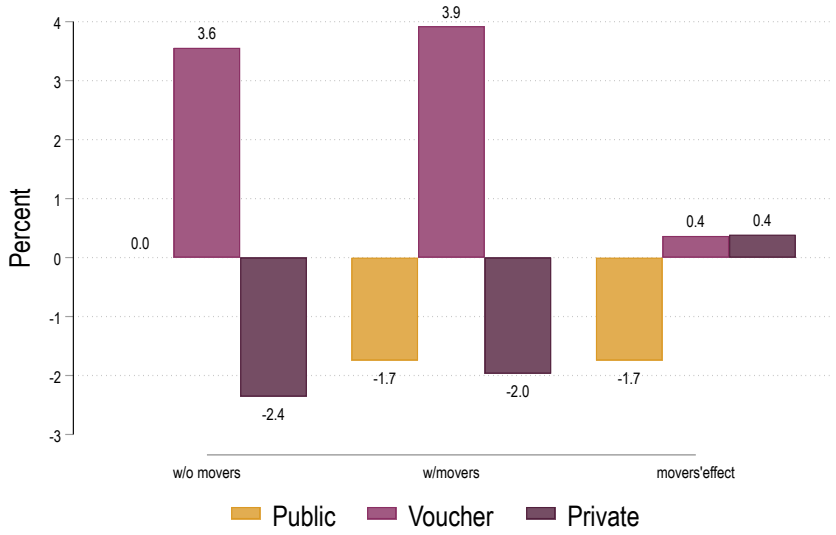
D. Application: Highly Selective Program

FIGURE A16. 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 (4) in the sample of students living in Santiago, where the outcome is an indicator for switching schools (Panel A), applying to at least one program (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% (*).



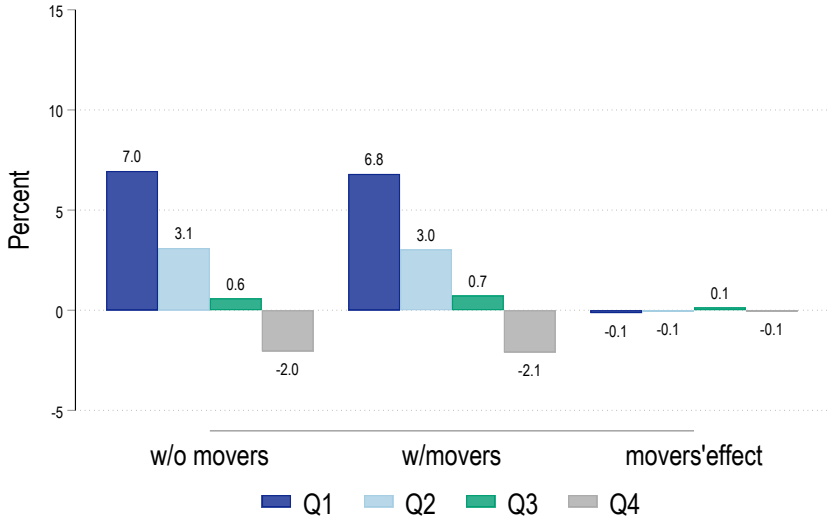
A. Overall System



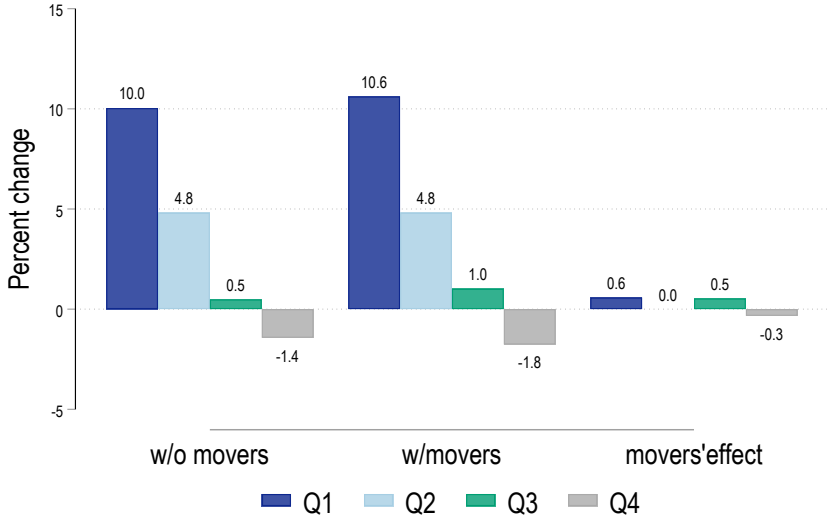
B. Tier 1 Universites

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

Note: This figure plots the changes in acceptance from Equation (6) and Equation (7) 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 prepolicy acceptance rates, the next three columns the change in the acceptance rate when students switched relative to the prepolicy 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.



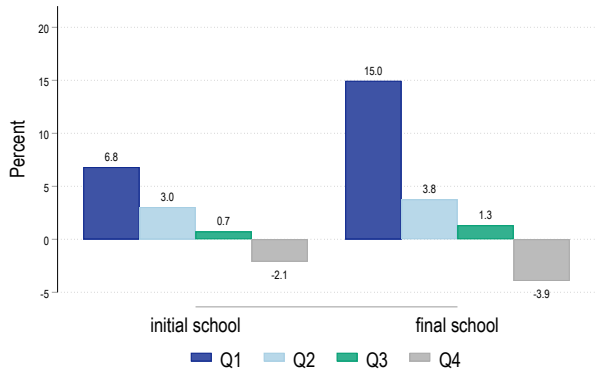
A. Overall System



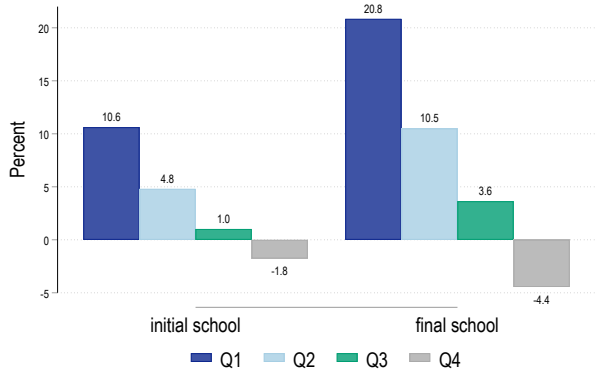
B. Tier 1 Universites

FIGURE A18. Distributional Effects of Strategic Responses to the RR Policy Disclosure by School Performance

Note: This figure plots the changes in admissions implied by Equations (6) and (7) for the overall system (Panel A) and for Tier 1 universities (Panel B). Each column represents the change in the number of admitted students by school performance. The first four columns report changes in admission rates when students are classified according to the school they attended at the beginning of twelfth grade; the next four columns report the same changes when students are classified by their school of graduation. The calculations hold the observed allocation of students fixed and vary only the school with which each student is associated. All estimates use the cohort applying for admission in academic year 2015.



A. Overall System



B. Tier 1 Universites

FIGURE A19. Relative Ranking Policy Impact Considering Starting and Ending Schools performance

Note: This figure plots the changes in acceptance from Equation (6) and Equation (7) 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 reclassifying students at the school they started twelfth grade, the next four columns calculate the same changes but classifying students by the school they graduated from. The calculation uses the real allocation of students and only change the school at which student is associated. 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 pp. 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% of the application score. However, this more consequential change was again only made 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.

[34] See `https://demre.cl/calendario/` for the 2023 application timeline.
[35] See `https://demre.cl/calendario/` for the 2015 process timeline.
[36] For details, see `https://demre.cl/psu/publicaciones/listado-2014`.

Appendix C. Model Derivations and Proofs

Proof of Proposition 1

Before the policy, $AS(g_i) = \gamma g_i + \theta$ does not depend on school. By (Unique Score), $\gamma g_L^* + \theta = \gamma g_H^* + \theta$, so $g_L^* = g_H^* \equiv g_0^*$. Since $AS_e(g_i) = AS_s(g_i)$ for all g_i, switching can never move a student from below the cutoff to above it, and no student switches. The capacity constraint (Capacity) becomes

$$\mu_L\big[1 - F_L(g_0^*)\big] + \mu_H\big[1 - F_H(g_0^*)\big] = K,$$

which pins down g_0^*. School e's share of students in the selective college is $\mu_e[1 - F_e(g_0^*)]/K$, which depends on the school-specific distribution F_e. □

Proof of Proposition 2

After the policy, under $\underline{r}_L < \underline{r}_H$ and $\bar{r}_L \le \bar{r}_H$, we have $AS_L(g) \ge AS_H(g)$ for all g, with strict inequality for $g \in (\underline{r}_L, \underline{r}_H)$. The unique-score condition (Unique Score) requires $AS_L(g_L^*) = AS_H(g_H^*) = AS^*$. Since $AS_L(g) \ge AS_H(g)$, a lower GPA suffices in school L: $g_L^* \le g_H^*$, with strict inequality whenever AS^* falls in the range where AS_L strictly dominates AS_H.

With $g_L^* < g_H^*$, school L's mass of students in the selective college is $\mu_L[1 - F_L(g_L^*)]$. Before the policy, it was $\mu_L[1 - F_L(g_0^*)]$. Since $g_L^* < g_0^*$ (shown below), $F_L(g_L^*) < F_L(g_0^*)$, so school L's share of the selective college increases. The capacity constraint is unchanged at K, so school H's share must decrease. Students displaced from the selective college move to the less selective college.

Before the policy, the cutoff solves $\mu_L[1 - F_L(g_0^*)] + \mu_H[1 - F_H(g_0^*)] = K$ with a common GPA threshold. After the policy, $g_L^* < g_0^* < g_H^*$ and the score function AS_L weakly dominates AS (the pre-policy function) in the bonus region. Therefore $AS_1^* = AS_L(g_L^*) > AS(g_0^*) = \gamma g_0^* + \theta = AS_0^*$. □

Proof of Proposition 3

When switching is permitted, some students from school H relocate to school L and obtain $AS_L(g_i) > AS_H(g_i)$. These switchers increase the mass of students with scores above any given threshold, which (holding K fixed) requires AS^* to rise weakly. If no student switches, the cutoff remains at its Proposition 2 value. Hence $AS_0^* \le AS_1^* \le AS_2^*$.

Set $\tilde{c}_i = 0$ for all i. All students from school H with $g_i \in [g_L^*, g_H^*)$ switch to school L, because $AS_L(g_i) \ge AS^* > AS_H(g_i)$. After switching, every student with $g_i \ge g_L^*$—regardless of original school—has a score at or above AS^*: either she was already in the selective college from school H (if $g_i \ge g_H^*$) or she switched to school L (if $g_L^* \le g_i < g_H^*$).

The capacity constraint after switching becomes:

$$\mu_L\big[1 - F_L(g_L^*)\big] + \mu_H\big[1 - F_H(g_L^*)\big] = K.$$

Before the policy, the constraint was $\mu_L[1 - F_L(g_0^*)] + \mu_H[1 - F_H(g_0^*)] = K$. Both equations have the

same form with a common GPA cutoff, so $g_L^* = g_0^*$. The composition of students in the selective college—$\mu_e[1 - F_e(g_0^*)]$ from school e—is therefore identical to the pre-policy allocation, regardless of whether $F_H = F_L$. Students displaced from the selective college by switchers are not excluded from higher education; they move to the less selective college.

In general, if a fraction q of students with a positive gain have switching costs exceeding U_i^S, the policy's compositional effect is proportional to q: the composition lies between the pre-policy allocation ($q = 0$) and the no-switching outcome of Proposition 2 ($q = 1$). □

Appendix D. Students relevant educational choice set

Recall a key component to calculate students' potential gain is their choice set. My primary analysis uses a 2-kilometer buffer. As a sensitivity analysis, Figure A20 presents the *median potential gain* distribution for 2- to 8-kilometer buffer using student's primary school as the center. The distribution of application score gain using different radius are similar.

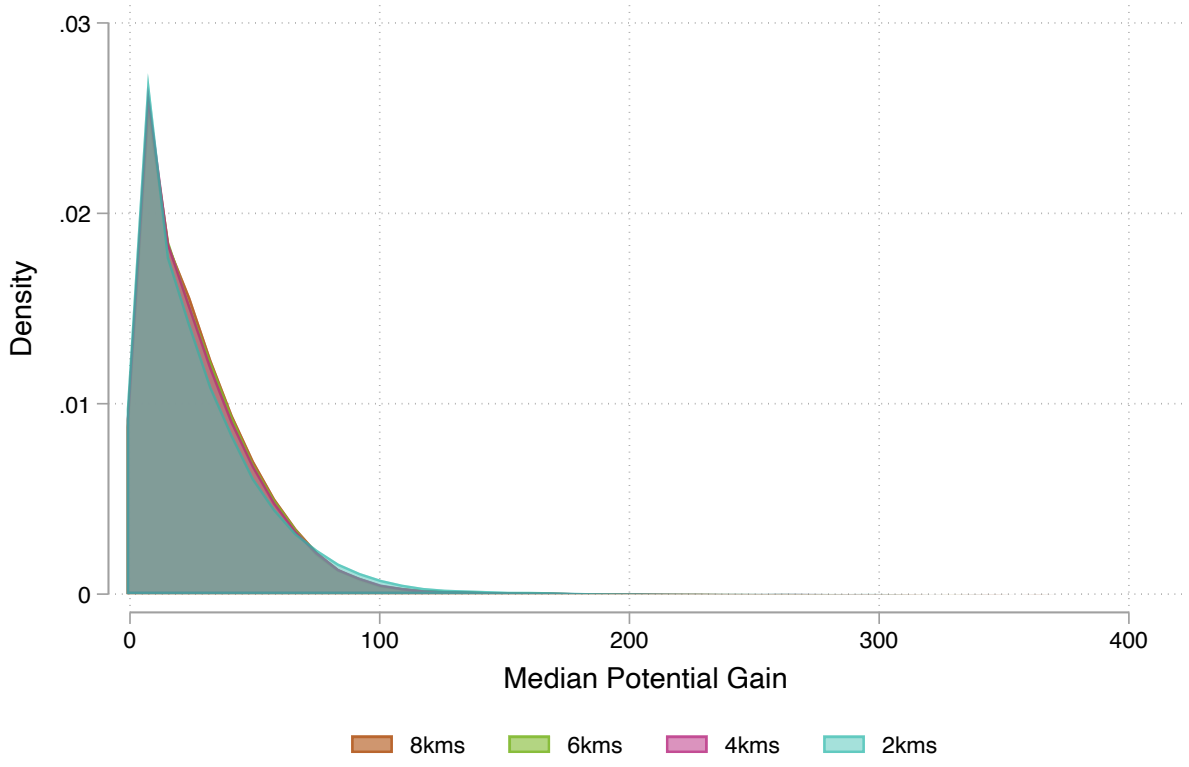


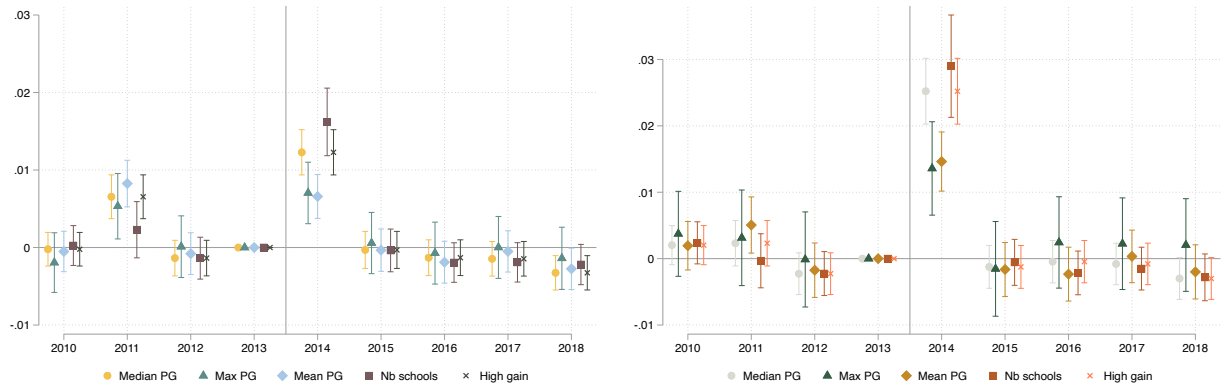
FIGURE A20. Positive Median Potential Gain Distribution.

Note: This figure plots the distribution of the median potential gain for four alternative definitions of the student's local school market, based on circular buffers of 2, 4, 6, and 8 km around the student's primary school.

Appendix E. Analysis using different treatment measure

Figure A21 presents the main event-study estimates from equation (4) under four alternative definitions of the treatment variable. The baseline specification (use throughout the paper) uses the median potential gain across schools in the student's local market. As described in Section 3, the baseline treatment variable is a binary indicator equal to one if student *i* has a positive median potential gain across schools in her local market. I consider four alternatives: (i) *maximum potential gain*, equal to one if the highest potential gain in the student's market is positive; (ii) *mean potential gain*, equal to one if the average potential gain is positive; (iii) *number of schools*, equal to one if at least 50% of schools in the student's market offer a positive gain; and (iv) *high potential gain*, equal to one if the median potential gain exceeds the mean among students with positive median gains.

The results are robust to these alternative definitions: all measures produce a similar pattern of flat pre-trends, a sharp increase in switching in 2014, and a return to zero thereafter.



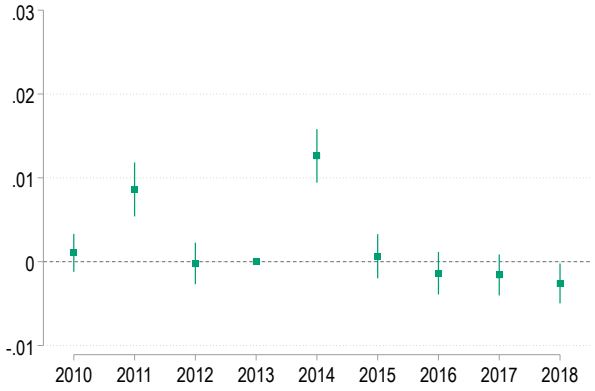
A. Chile B. Santiago

FIGURE A21. Impact of the RR policy disclosure on students' switching schools during twelfth grade for the sample of students always living in the same county

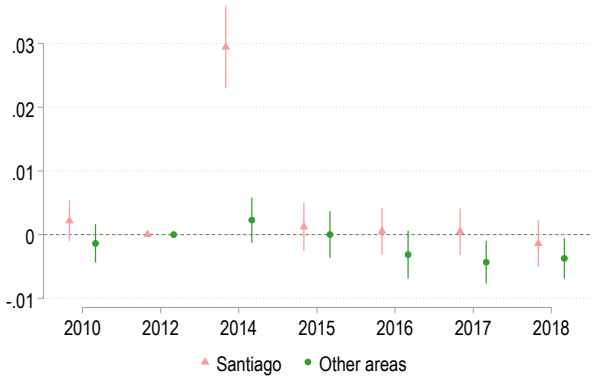
Note: This figure plots the coefficients from the regression of students' switching schools in twelfth grade on the interaction between having a potential gain, using different treatment definitions, and event-year dummies using equation (4). The event of interest is the release of the RR policy's formula 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.

Appendix F. 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 A22 present the impact of the RR policy disclosure (the event of interest) on students' switching schools decision using equation (4) in Chile (Panel A) and Santiago (Pnbel B) using the main treatment specification.



A. Chile



B. Santiago

FIGURE A22. 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 (4). 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.