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 the formula of a ranking-based affirmative action policy in Chile, I show that students with scope to benefit living in areas with competitive school and university markets are 2.5 percentage points more likely to transfer high schools during twelfth grade than similar students without such gains after the disclosure. These students are more likely to enroll in and graduate from selective college programs, with no increase in dropout. However, simulation-based counterfactuals show that strategic switching reduces the policy's effect on disadvantaged students' admission rates to the most selective universities by approximately 30%. College admission policies tied to the school students graduate from let a late change of school raise a student's chances of admission, shifting part of the policies' intended benefits away from the targeted students.

Key Words: School choice, college admission, college outcomes, behavioral responses

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1. INTRODUCTION

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

[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), and information policies to reduce uncertainty around college costs (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 are guaranteed admission to 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 those of previous graduating cohorts at their high school (Larroucau, Ríos Uribe, and Mizala Salces 2015; Reyes 2022) and offering direct access for high-performing low-income students (Tincani, Kosse, and Miglino 2025).

schools. Although students who switch schools increase their chances of enrolling in and graduating from selective programs, these strategic relocations reduce the policy's effect by displacing students of low socioeconomic status (SES) who would otherwise have been admitted to the most selective universities. I exploit a natural experiment generated by the disclosure of the formula of a relative ranking criterion in Chile's centralized college admission system. The disclosure in the documents students use while preparing for applications affected students in two key ways: it made explicit that the relative ranking score, which is part of the college admission score, is computed against the school from which a student graduates, rather than every school attended, 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 2014, the guidelines of Chile's centralized college admission system presented the formula of the relative ranking (RR) component, one of three elements of the admission score. The RR score transforms a student's GPA into an admissions bonus based on their rank relative to the previous three graduating cohorts at their school. Although the RR was introduced in 2012, the guidelines published before 2014 had described it only in prose, within the section on test-score normalization. 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, college applications, and college outcomes (Bodoh-Creed and Hickman 2018). Chile overcomes this limitation through rich administrative records that track students throughout their full educational careers and the centralized college application process. Second, Chile's centralized admission system operates under transparent and common rules, with students submitting ranked preferences over specific programs,[3] which allows observation of system-wide student–program 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

[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.

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 through college application, enrollment and graduation. These data allow me to identify 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 create two treatment measures for each student: a binary measure equal to one if the median potential gain across schools in the student's market is positive and a continuous measure equal to that median gain, standardized within the graduating cohort.[6] I also construct a measure of SES, based on the mother's education, and a measure of parents' aspirations from information reported in tenth-grade surveys. This dataset is used throughout the analysis to estimate the causal effect of the RR formula disclosure on twelfth-grade school switching and subsequent university admission, enrollment and graduation 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. I use the model's main predictions to structure the empirical analysis. For students to switch schools, the programs they apply to must be selective enough that a higher ranking score changes where they think they can be admitted; they must live in school markets with alternatives that would raise their ranking; and, 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 their school's distribution, particularly at high-threshold schools, where these thresholds generate larger potential gains from graduating elsewhere.

The second part of the paper estimates the causal effect of the RR formula disclosure on strategic school switching during twelfth grade and on subsequent college outcomes. Exploiting variation in students' potential gains from switching schools and a difference-in-differences event-study design, I show that the disclosure led to a meaningful increase in school transfers during twelfth

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

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

grade. Students living in areas with competitive school and university markets who stood to gain from switching schools were 2.5 p.p. more likely to transfer in 2014 than similar students without a gain, relative to 2013, corresponding to approximately 600 additional strategic transfers in a single cohort, and an increase of 177% over the predisclosure 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.[7] In robustness analyses, I show that the response remains positive and significant under alternative definitions of the potential gain and school markets.

Within Gran Santiago, the only metropolitan area with both competitive school and university markets, the response follows the model's predictions under both treatment measures: it is concentrated among students at high-performing schools and in the college-preparatory track. At high-performing schools, the disclosure raised the probability of switching by 5.0 p.p., or 3.6 p.p. per standard deviation of the potential gain. Although students respond at every level of the mother's education, students whose mothers did not complete high school have the smallest response. The largest observed difference is by parents' aspirations when students were in tenth grade: students whose parents expected them to attend college were 3.3 p.p. more likely to switch (2.1 p.p. per standard deviation) than similar students with no positive potential gain, while the rest barely responded. What seems to separate students' responses is less their family's resources (which correlate positively with parents' aspirations) than whether college is the plan. Still, most students with a potential gain did not switch, consistent with the value of a selective program being, for most of them, lower than the cost of switching and the value they place on their school and peers, and possibly with information frictions. Further analyses in the Appendix show that students in private and voucher schools barely responded and that students with no internet access at home responded less than students with internet at home.

I then examine how these strategic responses translate into postsecondary outcomes. For the same students, 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

[7]The magnitude of this response exceeds that documented by Cullen, Long, and Reback (2013) in the context of Texas' Top Ten Percent plan, where 211 students per cohort strategically chose less competitive high schools within their estimation sample, a number the authors describe as a lower bound — 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.

with positive gains are 1.1 p.p. more likely to enroll in and graduate from highly selective programs they entered in their first admission process, with no detectable increase in dropout or delay in graduation, suggesting that strategic school switching increased access to more selective programs without a measurable cost to 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 admission score formula and the centralized student-program matching algorithm to evaluate policy effectiveness. I simulate the 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. Relative to the 2012 admission weights, low-SES students are 3.5% more likely to be admitted to the most selective universities. Absent strategic switching, however, this effect would reach 5%, implying that strategic responses reduce the policy's effect by about 30%.

This study makes three contributions. First, I contribute to the literature on how college admission policies affect pre-college behavior. Previous research has shown that college admission policies affect pre-college outcomes such as effort (Grau 2018; Bodoh-Creed and Hickman 2018; Tincani, Kosse, and Miglino 2025; 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; González and Johnson 2018). Among them, the closest to this paper are Cullen, Long, and Reback (2013), who study the effects of the Texas Top Ten Percent plan, and Mello (2023), who studies Brazil's quota law. Both papers show that school-based admission rules change which high school students attend: students choose schools with lower-achieving peers in Texas and move from private to public schools in Brazil. In Chile, González and Johnson (2018) descriptively document that students whose grades placed them below the bonus range at their own school changed schools more often than students already receiving a bonus in their school, and that this gap widened after the RR was introduced.

On outcomes, Cullen, Long, and Reback (2013) do not observe college outcomes, and Mello (2023) observes only enrollment in federal universities and analyzes the effects separately for the self-selected samples of students who moved and those who stayed. By linking administrative data on the universe of high school seniors to centralized college application, enrollment, and graduation

records, I trace students from switching decisions through tertiary education outcomes and show that students with a potential gain reached more selective programs in their first admission process, with no detectable increase in dropout or delay in graduation. Using the potential gain as an instrument for switching, I also recover the effect for the students induced to switch by the RR formula disclosure. On the cost of the policy, Cullen, Long, and Reback (2013) compute how many minority students strategic movers displace from the top 10% pool and find the effect slight. I use Chile's centralized admission algorithm to simulate student-program matches under a no-switching counterfactual and find that strategic switching removes about 30% of the policy's effect for low-SES students at the most selective universities. On timimg and measurement, in Cullen, Long, and Reback (2013) and Mello (2023), students must move two to three years before applying to college to qualify for the preferential admission,[8] which can affect their GPA and preparedness for the college admission process. In my setting, students move at the last moment, during their final year of high school, most of them in its last months, which limits the scope for effects on learning given schools' different education production functions. Moving late also means that students largely know their GPA when they decide whether to switch, so I compute each student's score gain directly from the RR formula, using their GPA and the thresholds of the schools in their market, rather than relying on ability proxies or area-level exposure, the only measures available when the choice is made years in advance.[9]

Second, my results contribute 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

[8] In Texas, schools typically require transferring students to attend for some time before counting them in the class rank, so transfers after the spring of tenth grade may not be rewarded (Cullen, Long, and Reback 2013, p. 34). In Brazil, the quota applies only to students who attended all three years of upper secondary education in a public school (Mello 2023, p. 2).

[9] Cullen, Long, and Reback (2013) predict each student's probability of reaching the top 10% of each school from eighth-grade test scores, and describe their estimates as lower bounds due to "relatively crude proxies for individual incentives" (p. 44). Mello (2023) assigns each student the quota exposure of the federal universities in their microregion of residence.

relative performance within the school a student graduates from—induced strategic pre-college responses that reduced its effect for low-SES students at the most selective universities. In the simulation, students who switched gain places at highly selective programs, and most of those who lose such a place had a potential gain themselves but did not move, suggesting that the policy rewarded students who acted on the incentive.

Third, this paper also 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 show that when college admission scores depend on relative performance within the school a student graduates from, students in higher-performing schools may receive lower admission scores than those in lower-performing schools despite having identical GPAs. This feature creates an incentive to transfer to lower-performing schools to improve admission prospects.

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

2. CONTEXT: FROM SECONDARY TO HIGHER EDUCATION IN CHILE

Chile is a middle-income country with persistently high income and educational inequality.[10] 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.

[10] 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 (Education at a Glance, 2020).

2.1. Secondary Education

Chile has the highest secondary education graduation rate in Latin America, with relatively little variation across socioeconomic groups. In 2022, 89% of young people completed upper secondary education—85% among those in the lowest income quintile and 95% among those in the highest (CASEN 2022). 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.[11] 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.[12] 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 tertiary education, compared with only 25% from the lowest quintile in 2022.[13] 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.[14] Advocates for reform argued that students from low-quality schools face significantly

[11] School ranking was calculated as the average score on a standardized test taken by 10th-grade students in 2010, with 1 assigned to the school with the highest average.

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

[13] 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).

[14] Gabriel Boric, one of the leaders of this movement, was president of Chile from 2022 to 2026. See: `https://www.theguardian.com/world/2021/nov/18/a-fairer-chile-ex-student-leader-bids-to-reshape-country-in-divisive-election`.

lower chances of attending college—regardless of their individual ability or academic performance—due to systemic disadvantages tied to school quality. The RR policy examined in this paper was introduced in response to these concerns. It was designed to expand college access for high-performing students by accounting for the quality of the school they attended (see Section 2.3 for details).

2.2. College Application System

For the academic year 2013, all public universities and 16 of the 35 private universities in Chile admitted 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 program. DEMRE publishes them in a preliminary version around June of each year, six months before the applications are submitted, and a final version around October.[15] Although the weights are set internally by each university for each of its programs, subject to the requirement that they sum to 100 across the two mandatory PSU sections, the elective PSU subject, the standardized GPA, and the RR score, they do not vary substantially within universities.[16] For example, the Universidad de Chile (UCH), one of the two most selective universities in the country, offered 50 programs in the 2014 admission process, using only two different weights for the standardized GPA, and two for the RR across all the programs. Table A10 presents the average weight in the system for GPA and RR application scores; the three PSU tests account for the remainder.

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.[17] Second, they must take the national college entrance exam (PSU),[18] which is administered annually in

[15]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.

[16]University fixed effects account for 73% of the variance in the GPA weight and 83% in the RR weight in the 2014 admission process.

[17]The centralized system standardizes students' high school GPA (NEM) into a score ranging from 208 (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.

[18]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 500 and a standard deviation of 110, truncated at 150 and 850 points.

mid- to late December.[19] Third, applicants submit an ordered list of up to ten preferred programs. To support families in this process, the organization overseeing centralized admissions (DEMRE) maintains an official website with comprehensive information on procedures, timelines, and participating institutions.[20]

Applicants to the centralized system are matched to programs using a deferred acceptance (DA) algorithm.[21] In the period I study, students may rank at most ten programs and the two most selective universities (Universidad Católica de Chile and Universidad de Chile) further restrict where their programs may be ranked: only applications listed among a student's first four preferences are considered.[22]

Table A2 summarizes application behavior and match outcomes. Column (1) shows that more than 92% of applicants rank fewer than ten programs, and 45% submit at least five. Column (2) shows that 43% of applicants listing a program as their first preference are admitted to it, falling to 20% at the second preference, and to 12% at the third. Column (3) shows that, among admitted students, 88.5% are placed at one of their first three preferences and 93.9% within their first four.

2.3. The Relative Ranking Policy

In June 2012, to support students from low-ranked high schools with strong grades but lower PSU scores, the Consejo de Rectores de las Universidades Chilenas (CRUCH) introduced a new component to the college admission criteria: the *Relative Ranking* (RR) bonus.[23] 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 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

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

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

[21] 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.

[22] Source: DEMRE's annual publication *Oferta Definitiva de Carreras, Vacantes y Ponderaciones*.

[23] This policy was supported by the Chilean economists Dante Contreras, Franisco Meneses, and Sebastián Gallegos based on their study "Determinantes del desempeño universitario: Importa la habilidad relativa?" (Contreras, Gallegos, and Meneses 2009).

RR score equals their standardized GPA score (SGPA). When the GPA lies between that average and the highest GPA observed among those cohorts, the student receives a proportional bonus. Finally, students whose GPA exceeds the highest GPA of the prior three cohorts receive the maximum RR score of 850 points. Figure 2 illustrates this mapping: the blue line depicts the linear transformation from GPA to SGPA, while the red line shows the nonlinear relationship between GPA and the standardized RR score. In the figure, $\underline{r}_s$ denotes the average GPA across the three 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 the documents available on the university application system's official website, together with press coverage from the period, to establish when the relevant information for students' decision making was public and in what form. Although the policy was implemented in 2012,[24] the official guidelines did not clearly explain how the relative ranking (RR) was computed until 2014. The policy itself was discussed openly from the start, with some experts supporting it and others raising its potential unintended consequences.[25] However, clear information about the formula used to calculate the RR score was only available for the cohort graduating in 2014.

Figure A26 reproduces the corresponding sections of the official guidelines for the 2014 and 2015 admission processes (i.e., students applying in 2013 and 2014). In the earlier document the ranking score is described in prose, within the section on test-score normalization. In the later one it has its own section, which states what happens to students below their school's historic average, and which includes a figure plotting the ranking score against a student's GPA. The later document also makes explicit that the comparison is with previous cohorts of the school from which the student graduates, rather than with all schools attended during high school. In August 2014, the rule was changed, effective from the 2016 admission process, to weight scores across all schools attended, limiting the gains from last-minute switches.

It is worth emphasizing that the introduction of a clearer description of the RR policy in the guidelines does not constitute direct evidence on families' information sets. What it establishes is

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

[25] For supporters, see, for example, "Los datos que respaldan la utilidad del ranking de nota", published by CIPER on July 17, 2012: `https://www.ciperchile.cl/2012/07/17/los-datos-que-respaldan-la-utilidad-del-ranking-de-notas/`. For critics, see, for example, "Lo que debes saber sobre la incorporación del ranking de notas," published on the Universidad de Chile news site on July 6, 2012: `https://uchile.cl/noticias/83099/lo-que-debes-saber-sobre-la-incorporacion-del-ranking-de-notas`.

that the incentive was legible in the document students consult only from 2014 onward, which is consistent with the identifying assumption that this marked an inflection point in students' ability to act on the policy. Throughout the paper I do not rule out the possibility that the information was also spread through other types of sources, such as peers and schools; what I argue is that the clarification in the guidelines made such diffusion possible.

2.4. Tertiary Education

Table 1 summarizes key characteristics of postsecondary 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 program is roughly 46 students across institution types, with larger cohorts in private institutions. Average annual tuition (in Chilean pesos) is similar for public and private universities within the centralized system but tends to be higher than at institutions outside it. Public and private universities also display comparable distributions of STEM programs and accreditation levels.

Throughout the paper, I classify selectivity at two levels. Universities follow the tiers of Kapor, Karnani, and Neilson (2024), which group them by the mean admission score of the students admitted in 2012. Tier 1 consists of the two most prestigious and selective universities in the country, the Universidad de Chile and the Pontificia Universidad Católica de Chile, and tier 2 of the Universidad de Santiago de Chile, the Universidad de los Andes, and the Universidad Adolfo Ibáñez. All five offer their programs in the metropolitan area of Gran Santiago, and the Universidad Adolfo Ibáñez, whose main campus is in Viña del Mar, is the only one in the most selective tiers offering programs in another metropolitan area outside Gran Santiago. Similarly, programs are ranked by the mean admission score of the students they accepted in the 2014 admission process, the last before the RR formula disclosure, and a program is highly selective if it is in the top quartile of that ranking among the 1,419 programs offered that year. Appendix K describes these and other program characteristics.

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

3. CONCEPTUAL FRAMEWORK

I develop a simple theoretical model to identify which students have incentives to game the policy by switching schools and to assess how 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.

3.1. 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 the switching decision. Each student is characterized by a GPA $g_i \in (\underline{g}, \bar{g})$ and an initial high school $s \in \{L, H\}$.[27]

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.

[26] 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.

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

This structure reflects Chile's centralized admission system, in which students submit a ranked list of program.[28] Empirically, I show in Section 6 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:[29]

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

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 L.[30] A student starting twelfth grade in school s has a potential gain in their application score from switching to school e if

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

[28]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.

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

[30]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 $\bar{r}$ (see Table A1). Second, I do not impose any restrictions in the empirical analysis when calculating students' potential gains.

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

3.2. 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).[31] Students pay a direct cost $c_{ise} \geq 0$ when switching from school s to school e and derive school-specific utility $b_{is} > b_{ie}$.[32] 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.

3.3. 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:

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

[31] 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.

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

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

$$\text{(Capacity)} \qquad \mu_L\left[1 - F_L(g_L^*)\right] + \mu_H\left[1 - F_H(g_H^*)\right] = K.$$

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.

4. DATA

4.1. Administrative Data Sources

This paper combines five 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 program information, including the weights assigned to each admission score component, the number of available seats, and program-level details. The second dataset comes from the Higher Education Information Service (SIES) of MINEDUC, which records the yearly enrollment and graduation records of every student in higher education; from it I build persistence, dropout, and graduation outcomes.

The third 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 program preferences, admission results, and household characteristics at the student level.

The fourth 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. One limitation of the SIMCE data is that the test and questionnaire were administered in 2006, 2008, 2010, and every year from 2012 onward, so students who finished twelfth grade in 2011 and 2013 have no student-level characteristics or tenth-grade standardized scores, and those two cohorts are excluded from any analysis that relies on SIMCE data.

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

4.2. Data Limitations

Although Chilean administrative data offer rich student-level information, the data used in this paper have two main limitations. First, I do not directly observe students' 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 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-km buffer, and test buffers of up 8-km.[33] These buffers are intended to capture the schools a student would consider, and the distances students actually travel to school support that choice. In Gran Santiago, half of students start twelfth grade in a school within 2 km of their

[33]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).

primary school and two thirds within 4 km. The median traveled distance is 2 km (Figure A4). Consistently, 78% of students attend a school in the same county in primary and secondary school (Figure A3).[34] Both shares are stable across cohorts and do not differ by treatment status. Moreover, in Appendix D, I re-estimate the main analysis using buffers of 4, 6, and 8 km, and the results are robust.

4.3. Variables Construction and Descriptive Statistics

Using the census of schools and students from MINEDUC for cohorts entering twelfth grade between 2010 and 2018, I construct two variables that identify the treatment status and one of the main outcomes of interest. First, I create the treatment variable—the *positive potential gain* indicator—which measures whether a student could experience an increase in their college admission 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) for applications and admissions, and from SIES for enrollment, persistence, and graduation. 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% (Kapor, Karnani, and Neilson 2024). Second, because college completion in

[34]The average size of a county in Gran Santiago is approximately 63.4 km^2.

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 tier 1 university (PUC and UCH) within their three most preferred programs. Among all the applicants, almost 80% are accepted to one of the programs they ranked. When considering acceptance and enrollment rates, 11% of the applicants are accepted into a tier 1 university, and a similar share enroll in that type of institution. Finally, 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.[35] 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 A2).

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 4.2 for data limitations and Appendix D for validations on how relevant markets are calculated).

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

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 2.3 for details), I can calculate the median potential gain (MPG) for any cohort, including those that applied before the policy was implemented. Additionally, as a 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 error in constructing the MPG or the school markets must be nondifferential with respect to unobserved determinants of switching and 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 78% 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 constructed RR score, I compare the calculation using the formula presented in Section 2.3 for cohorts graduating from 2012 to 2015 against the one reported in administrative records.[36] Figure A5 presents the distribution of these differences. The mean difference between the two measures is 0.20 points on a scale that runs from 208 to 850 and has a standard deviation of 125, and the median is zero; 59% of the students are within 5 points of the official score and 79% within 10. I also checked whether the differences are systematic for particular schools and found no evidence that they are. Although the constructed score is not perfect, its error is centered at zero and small relative to the score itself, and I treat it as classical measurement error throughout the paper.

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 ($positive_gain = 0$). I also use a continuous measure, the MPG standardized within each graduating cohort. On average, 35% of twelfth-grade students nationwide have a positive median gain within their relevant market. Among students in Gran Santiago, the share is slightly higher, at 39%.

Figure 4 plots the share of students with positive gain by year, and Figure A6 compares the distribution of median potential gains for students in Gran Santiago 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 on strategic relocation during twelfth grade. Finally, in Tables 2 and 3 Columns 4-7, I present the main descriptive statistics for my sample of high school graduates and applicants to college separately for students with no gain (Columns 4 and 5) and with gain (Columns 6 and 7).

II. **Switching Schools during Twelfth Grade**

I focus on students' switching decisions in twelfth grade because the policy implementation created incentives to relocate at the last possible moment (see Section 2.3). The Chilean context provides

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

two institutional features that allow me to distinguish transfers occurring at the beginning of the academic year from those occurring during it.[37] First, enrollment is recorded in March (the start of the academic year) and again in December (when grades are published). Second, students are permitted to transfer schools during the year up to two months before it ends, 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), Gran Santiago (Panel B), high-performing schools nationwide (Panel C), and high-performing schools in Gran 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 Gran Santiago account for 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 3).

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 when the RR policy formula was clarified in students' guidelines. 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.

[37] 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.

5. EMPIRICAL SPECIFICATION

This section outlines the identification strategy used in this paper. The main strategy (5.1 and 5.2), a difference-in-differences (DD) event-study design, identifies the causal effect of the RR policy disclosure on students' strategic behavior and college admission outcomes among twelfth-grade students with and without high potential gains.

5.1. Switching Schools during Twelfth Grade

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

(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 who differ in their median potential gain within the same twelfth-grade cohort, net of time-invariant differences across schools and GPA deciles. Students differ in potential gain for two reasons: their primary school locations place them in different local school markets, and their own standing in the grade distribution places them at different distances from the ranking thresholds of the schools in that market.

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. Grade inflation is perhaps the most direct threat to this second assumption. Because treatment is measured from grades, school inflating differentially could change which students are classified as having a positive gain. Appendix H re-estimates Equation 4 on measures rebuilt from deflated grades, and the estimates are essentially unchanged.

5.2. 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:

$$\begin{aligned} (5) \quad college_in_outcome_{istm} = &\sum_{\tau=2011 \tau \neq 2013}^{2016} \beta_\tau \mathbb{1}\{t = \tau\} \cdot positive_gain_{ism} + \\ &+ \beta_{pg} \cdot positive_gain_{ism} + \delta_t + \delta_s + \delta_{g\,pa_decile} + \varepsilon_{istm}, \end{aligned}$$

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.

Recovering a local average treatment effect (LATE) requires the parallel trend assumptions stated in Sections 5.1 and 5.2 to hold jointly, together with two further assumptions (Hudson, Hull, and Liebersohn 2017). The first additional assumption states that the RR formula disclosure led no student to stay who would otherwise have moved (*monotonicity*), while the second additional assumption requires that a positive potential gain affects college outcomes only through the decision to switch schools (*exclusion restriction*. For the exclusion restriction to be violated, it would be necessary that students who stood to gain would have different potential college outcomes because of it. Although unlikely, two violations of this assumption could occur. First, students might exert higher effort because they learn they have a positive potential gain in their school market. The switching timeline minimizes this concern, since the majority move three months before graduating, and any change in effort would have had close to zero effect on their GPA or the national exam. Second, the potential gain could be correlated with neighborhood characteristics that affect the potential outcome. I add county fixed effects in the regression in Appendix X to account for correlation between the instrument and neighborhood characteristics.

6. RESULTS

6.1. Switching Schools during Twelfth Grade

I begin the analysis by estimating the impact of the RR policy disclosure–the event of interest–on students' decisions to switch schools, using equation (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 treatment measure and the event-year dummies, for both the discrete measure, an indicator for having a positive potential gain, and the continuous measure, the standardized gain. Figure 6 presents results for the full national sample of twelfth-grade students, each panel reporting the main sample and a restricted sample of students who lived in the same county during primary and secondary school, while Figure 7 shows results from separate estimations for the three largest metropolitan areas and, in its last two panels, for Gran Santiago under three samples. 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 more likely to switch schools during twelfth grade relative to the year before the RR policy formula was made public. This effect represents an increase of 72% relative to the sample mean (0.017) in the prepolicy period (2010–2013). Under the continuous measure, a one standard deviation higher potential gain raises the likelihood of switching by 0.7 pp, or 40% of the prepolicy mean. Both measures show the same response, consistent with how they are created, though their magnitudes are not directly comparable since the standardized measure is centered on the average gain (equal to 4.2 RR points). The coefficients for the years preceding the policy release are close to zero and statistically insignificant, except for 2011. As discussed in Section 2, that year's increase is explained by the nationwide student protests, which kept many schools closed for several months and led some students to change schools for reasons unrelated to the RR policy, which was not yet under discussion.[38] After 2014, the estimated difference in the likelihood of switching schools disappears, consistent with the subsequent policy change under which students were compared not only within the school from which they graduated but across all schools they attended (see Section 2.3 for details). These estimates pool the whole country, where the three main metropolitan areas (Gran Santiago, Gran Concepción, and Gran Valparaíso) account for more than 50% of the population and Gran Santiago alone for almost 40%.

The theoretical framework in Section 3 highlights the conditions that create the environment for students to switch schools. Equation 3 shows that for switching schools to be worthwhile, two conditions have to hold together: the student must have a school within reach where graduating

[38] Appendix L separates the two episodes by their timing and their geography: the 2011 switches concentrate in July, the month after the occupations began, and in the counties where the protests were most intense outside Gran Santiago, while the 2014 response concentrates in August and in Gran Santiago.

would raise their ranking score, and must be applying to programs selective enough that a higher score changes where they think they can be admitted. The three largest metropolitan areas hold 55% of twelfth graders, and only Gran Santiago satisfies both. Within 2 km its students have 18 alternative schools on average, against 10 in Gran Concepción and 17 in Gran Valparaíso, and the median gain from those alternatives is 4.9 RR points in Gran Santiago, against 5.4 and 0.9 in Gran Concepción and Gran Valparaíso, respectively. On the university side, Gran Santiago ends with only 7% of its seats unfilled, against 18% and 12% in the other two areas; 14% of Gran Santiago's programs are among the hundred most selective in the country, against 6% and 5% for Gran Concepción and Gran Valparaíso. Finally, 71% of applicants from Gran Santiago list a program at a tier 1 or 2 university among their first five preferences, against 7% and 22% in the other two areas. Appendix I presents the differences across metropolitan areas in more detail.

Estimating equation 4 separately for the three largest metropolitan areas confirms that students in areas where both conditions hold reacted to the disclosure of the policy: the response is confined to Gran Santiago, where having a positive gain increases the likelihood of switching schools during twelfth grade by 2.5 pp relative to the year before the RR policy formula was made public, corresponding to a 177% increase relative to the 2010–2013 mean of 1.4%. The corresponding estimates are −0.14 pp in Gran Concepción, and −0.20 pp in Gran Valparaíso, neither distinguishable from zero. A formal test rejects equality with the Gran Santiago coefficient in both cases. The continuous measure shows a very similar pattern: one standard deviation higher potential gain only raises the probability of switching in Gran Santiago, the metropolitan area that has schools that will give students a larger RR score and selective universities for which the points are valuable.

For students in Gran Santiago, the coefficients for the years preceding the policy release are close to zero and statistically insignificant, including 2011. Consistent with strategic behavior, and as in Figure 6, after the rule change—effective for students graduating from 2015 onward, 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. The rest of the analysis therefore focuses on Gran Santiago, the only area where the school markets offer students alternatives worth moving to and selective universities make a higher ranking score matter.

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 relocations that occur at the beginning of the academic year, with results presented in Figure A7. 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. The results indicate that the response was concentrated among students at high-performing schools and in the college-preparatory track, and among students whose parents expected them to attend college.

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[39]—as predicted by the theoretical framework—as well as to schools with a poorer socioeconomic composition, closer proximity to their home, lower college enrollment rates, and weaker academic performance. Figure **??** 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 **??**-**??** 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.

[39] 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.

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

In this section, I estimate the impact of the RR policy disclosure on students' postsecondary outcomes using Equation (5). For students in Gran 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 and graduate from highly selective programs, with no detectable increase in dropout or delay in graduation.

Figure 12 plots the coefficients on the interaction between the positive potential gain indicator and event-year dummies for students living in Gran Santiago (the sample covers cohorts graduating between 2011 and 2016; see Section 4.3 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 1.1 p.p. likelier to be admitted to a highly selective program and 0.8m p.p. more likely to enroll at a tier 1 or 2 university in 2014, the year following the RR formula disclosure. The tier 1–2 programs they enter are the highly selective (0.9 pp) and high-return (0.8 pp) ones, all significant at 5% or better. There is no effect on enrollment at tier 1 universities alone, nor in traditional or STEM programs (Figure A15).

I also examine whether the policy disclosure affected students' application behavior.The disclosure did not change whether students apply (−0.1 pp, not significant), but it changed what they list among their first three preferences: students with a positive potential gain are 1.1 p.p. more likely to list a highly selective programs with no effect on tier 1–2 universities, high-return, traditional, or STEM programs (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 (5) 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 leaving their first program. They are, however, 1 p.p. more likely to graduate from the program they applied to, and 1.1 p.p. more likely to graduate from a highly selective program. The effect on graduating from any program is 0.3 p.p. and not significant.

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, 2.5 p.p. more likely 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 present among the population applying to college.

These estimates compare students with and without a positive potential gain, and in a centralized system that clears, the two groups are not completely independent. Conditional on similar preferences, a student who raises their admission score takes a place another student would have held, so the comparison group is itself affected by the treatment. What the estimates measure is therefore a contrast between the two groups that includes this displacement, rather than the effect on a treated student holding the admission cutoffs fixed. Section 7 calculates distributional effects through a simulation exercise where I compute the admission of each student who applied in the 2015 admission process with and without movers.

Using these results, together with the causal effects of a positive potential gain on college-related outcomes estimated above, I recover the Local Average Treatment Effect (LATE) for the group of students who switched schools in response to the RR policy release (the compliers). 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. Students who switched schools during twelfth grade in response to the RR score formula release are 44 p.p. more likely to graduate from a highly selective program, which is the 1.1 p.p. effect of a positive potential gain on graduation from a highly selective program over the 2.5 p.p. first stage.

A back-of-the-envelope calculation expresses the return to switching in monetary terms using the program-specific average monthly income four years after graduation (see Section 4 for the data description).[40] A highly selective program pays 464,000 Chilean pesos a month more than a

[40] I do not consider a discount rate or promotions over the work cycle in this calculation.

program in the adjacent selectivity quartile.[41] Switching schools was therefore worth about 204,000 pesos a month to the students who switched, or around 2,500 US dollars a year and some 87,000 dollars over a 35-year career. Using the average program as the comparison instead, the return to switching would have been a little more than 100,000 dollars, which represents around three times what an average worker accumulates over a working life.[42]

7. Effect on Policy Effectiveness

I now examine the distributional effects of students' strategic school switching by simulating student–major matches under two scenarios: one allowing school switching and another in which no student switches schools. Focusing on the cohort applying to college for the 2015 academic year, I show that students whose mothers have less than a high school diploma are negatively affected by switches, experiencing 30% 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.

7.1. Simulating Application Scores and Matching Algorithm

I recover the distributional consequences of strategic switching by simulating the admission process directly.[43] I compare who was actually admitted in the 2015 admission cycle with who would have been admitted had no student switched schools. I construct counterfactual application scores by recomputing each student's Relative Ranking score as if they had graduated from the school they attended at the start of twelfth grade, holding their GPA and PSU scores fixed. I then re-run the DA algorithm on these scores to obtain counterfactual matches. Because only the RR

[41] In pesos of September 2025.

[42] Cecilia Arroyo A., "Ahorro acumulado de los nuevos pensionados alcanza a $34 millones promedio en las AFP", *Diario Financiero*, 16 March 2023, reporting figures from Ciedess for new pensioners in January 2023.

[43] The RR policy timeline coincides with other changes to the admission system, which makes an event-study design difficult to apply to admission outcomes (see Figure A8 and Kapor, Karnani, and Neilson (2024)). A design such as regression discontinuity would capture only the effect on marginal students, whereas the object of interest is the effect across the full cohort.

score changes in this exercise, any difference in the composition of admitted students between the two allocations is attributable to school switching.

To express the effect of switching as a share of the policy's intended effect, I benchmark both allocations against the admissions the cohort would have received under the prepolicy weights of the 2012 admission cycle. Because the ranking component received no weight in 2012, the benchmark is identical under either school assignment. Thus, for students applying during the 2015 cycle, in group g and program d the changes are calculated as follow:

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

and

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

where $\Delta^{BE}_{g,2015,d}$ is the change in admissions the RR policy would have produce for group g in program d acceptance had no student switched schools; $\Delta^{SW}_{g,2015,d}$ is the change it actually produced for group g in program d acceptance had no student switched schools. Therefore, the contribution of strategic switching is their difference:

$$\Delta^{ST}_{g,2015,d} = \Delta^{SW}_{g,2015,d} - \Delta^{BE}_{g,2015,d}. \tag{8}$$

Because both terms in (8) share the same denominator, Δ^{ST} is the difference in admitted students between the two 2015 allocations, expressed relative to the 2012 benchmark.

Simulations limitations. This exercise has three limitations. First, for the difference across the two 2015 student-program allocations to depend only on relocation, switching schools during twelfth grade cannot change students' effort on the admission exam, and therefore their scores. Most switchers spend less than a full academic year in their destination school (see Figure **??**), which leaves little scope for the learning required for the exam to be affected, especially in a context where students start preparing as early as ninth grade. Further, Fajnzylber, Lara, and León (2019),

who study the effects of the RR policy introduction, find that the ranking bonus raised recorded GPA without corresponding gains in standardized test scores or admission-exam performance.

Second, although relocation is unlikely to affect a student's GPA through effort, for the same reasons it does not affect exam scores, grades and thresholds can nonetheless be affected by the policy through grade inflation. Fajnzylber, Lara, and León (2019) document that the ranking bonus raised grades through school-level grading responses, and by more in schools facing stronger incentives, so both a student's GPA and the thresholds of the schools reflect that response. For the comparison between the two 2015 allocations this is a feature of the environment rather than a source of bias: each school's thresholds are held at their observed values and only the school assignment changes. Grade inflation does limit the benchmark, which asks how the cohort would have been allocated absent the bonus using inputs the bonus had already altered (i.e., student's GPA). The benchmark therefore isolates the effect of the formula on allocations rather than a full behavioral counterfactual.

The third limitation is that application portfolios are held fixed across allocations. The DA matching algorithm is strategy-proof when students may rank every program (Dubins and Freedman 1981; Roth 1982). In the case of Chile, students can rank up to 10 preferences and in the 2015 application cycle more than 92% of applicants did not reach the cap (see Table A2), which allows preferences to be recovered following Abdulkadiroğlu et al. (2020). That speaks to how students order their lists, not to which programs they include. Application portfolios respond to perceived admission probabilities (Agte et al. 2024; Larroucau et al. 2025), and students with positive potential gains applied more ambitiously after the disclosure (see Section 6.2). Additionally, since the two most selective universities consider applications only within a student's first four preferences, the bonus can move a program up a list as well as onto it. 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 strategic behavior, making the estimated effect conservative.

7.2. Assignments and Distributional Effects under the Simulation Analysis

The Relative Ranking (RR) policy was designed to expand college access for students from lower socioeconomic backgrounds, who are disproportionately enrolled in public and lower-performing high schools (see section 2.3). Figure 13 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 leaves aggregate admission almost unchanged within each SES group. Among low-SES students, 155 lose a place, 155 others gain one, and a further 400 are admitted in both allocations but to a different program; the corresponding figures are 396, 380 and 986 for medium-SES students, and 260, 253 and 799 for high-SES students. The reallocation is therefore compositional rather than aggregate.

Now, 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).

7.3. Discussion

Many affirmative action policies in higher education define eligibility using students' high schools. This approach is motivated by the close relationship between school quality, school type (public, charter, or private), and students' socioeconomic backgrounds. However, 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 within their analysis sample, 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 from Tier 1 universities—about 1 in 21 of those who would otherwise have been admitted—while 19 others gain a place, for a net displacement of 8. Those places accrue to the top of the distribution: high-SES students gain a net 17 places at Tier 1 universities while medium-SES students lose 17. 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.

8. CONCLUSION

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

The results indicate that strategic responses are concentrated among students attending high-performing schools and among those whose parents held high educational aspirations. These students systematically targeted destination schools in ways that increased their college application scores, consistent with the incentives embedded in the policy design. I further show that students who switched schools were 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

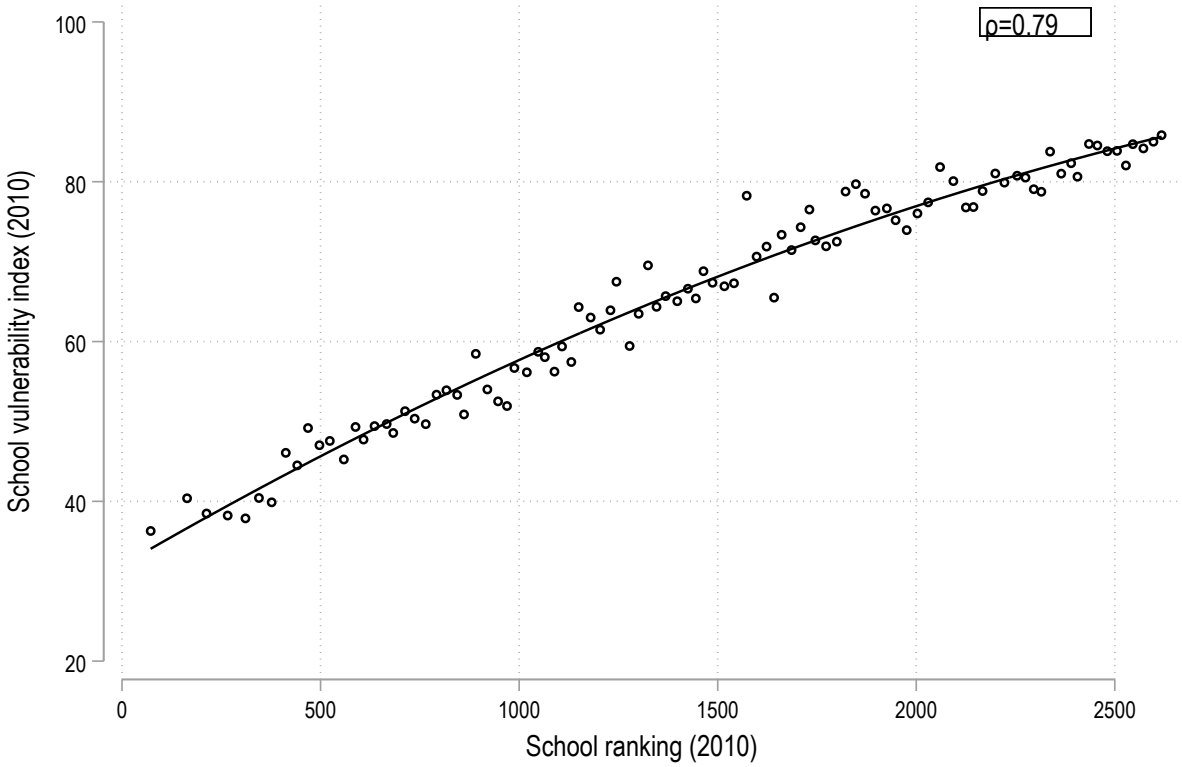


FIGURE 1. School Vulnerability Index & School Ranking

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.

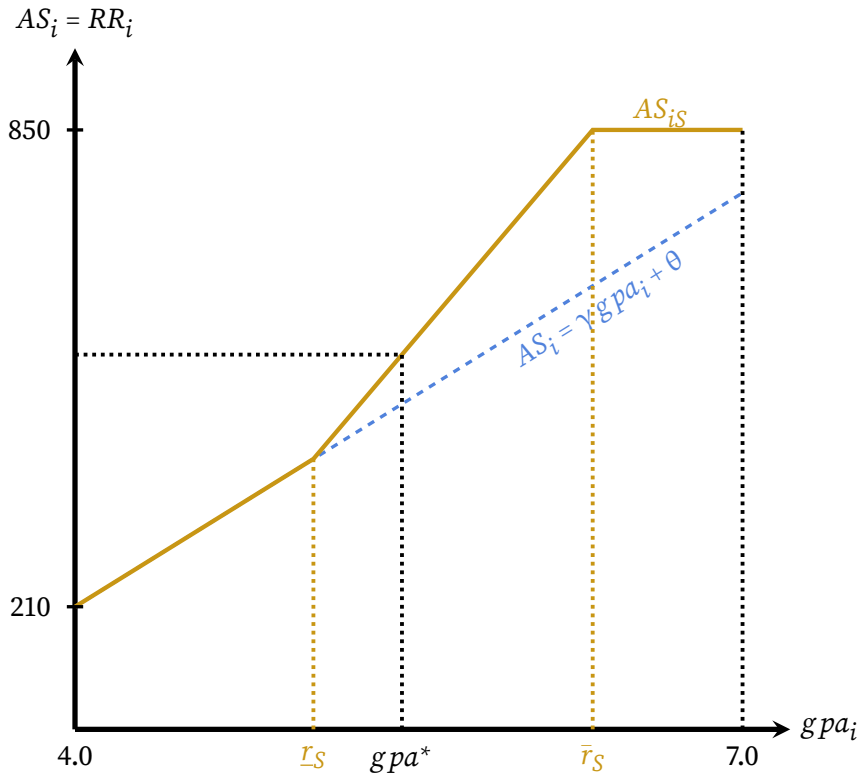


FIGURE 2. Construction of the Relative Ranking Score

Note: This graph depicts the formula used in Chile to calculate the relative ranking score (RR). The horizontal axis is the student's GPA measured on Chile's 1.0 to 7.0 grading scale and shown over its effective range, from 4.0 (the minimum passing grade) to 7.0. The vertical axis is measured on the 210 to 850 scale used for university admission scores. The blue dashed line shows the formula for the student's standardized GPA (SGPA) as a linear function of the student's GPA. The yellow solid line represents the non-linear formula to calculate the RR score as a function of GPA. $\underline{r}_S$ represents the mean GPA of the three previous cohorts who graduated from school S, and $\bar{r}_S$ the highest GPA among the three previous cohorts. The two thresholds split the graph into three regions. Below $\underline{r}_S$, the RR score coincides with the SGPA: students whose GPA falls below their school's historical mean receive no bonus. Between $\underline{r}_S$ and $\bar{r}_S$ the RR score rises more steeply than the SGPA, and the vertical distance between the two lines is the bonus the RR policy adds. At and above $\bar{r}_S$, the RR score is capped at 850. gpa^* marks an illustrative student, with dotted lines tracing the RR score that student receives.

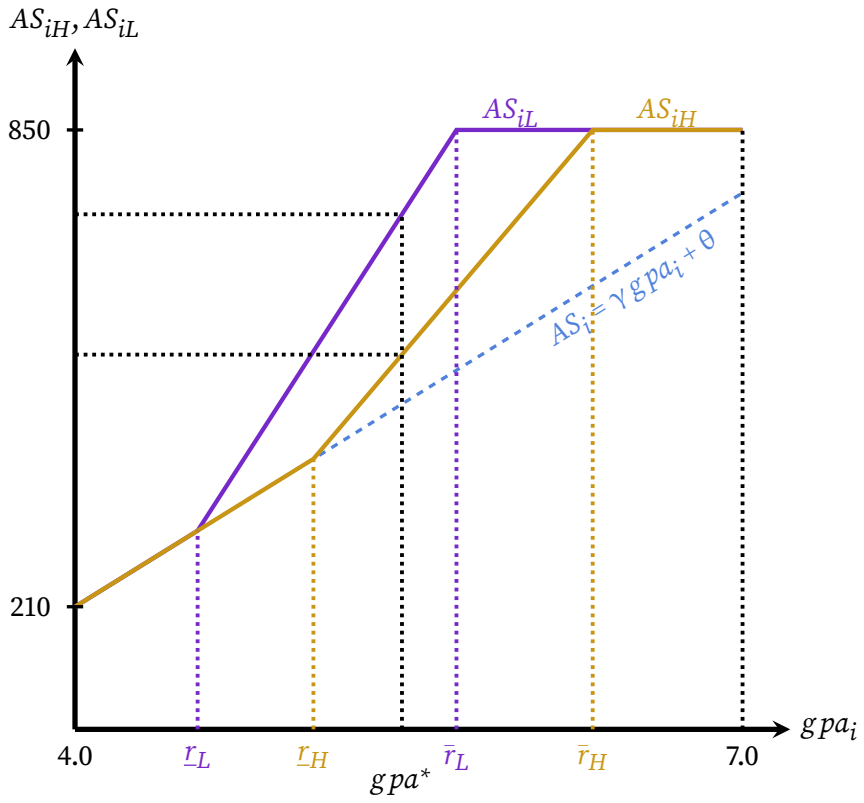


FIGURE 3. Relative Ranking Score at Two Schools: Thresholds in the Same Order

Note: This graph depicts the formula used in Chile to calculate the relative ranking score (RR) for two schools with different thresholds. The horizontal axis is the student's GPA measured on Chile's 1.0 to 7.0 grading scale and shown over its effective range, from 4.0 (the minimum passing grade) to 7.0. The vertical axis is measured on the 210 to 850 scale used for university admission scores. The blue dashed line shows the standardized GPA (SGPA), which depends only on the student's own GPA and is therefore common to both schools. The yellow solid line shows the RR score for students graduating from school H, and the purple solid line the RR score for students graduating from school L. $\underline{r}_L$ and $\underline{r}_H$ represent the mean GPA of the three previous cohorts who graduated from schools L and H respectively, and $\bar{r}_L$ and $\bar{r}_H$ the highest GPA among those same cohorts. Here the thresholds preserve the same order on both margins, $\underline{r}_L < \underline{r}_H$ and $\bar{r}_L < \bar{r}_H$. Because school L's thresholds are lower, its students begin earning a bonus at a lower GPA and reach the 850 cap sooner. The dotted lines at gpa^* show the consequence: two students with the same GPA receive different RR scores, and the one graduating from school L receives the higher score.

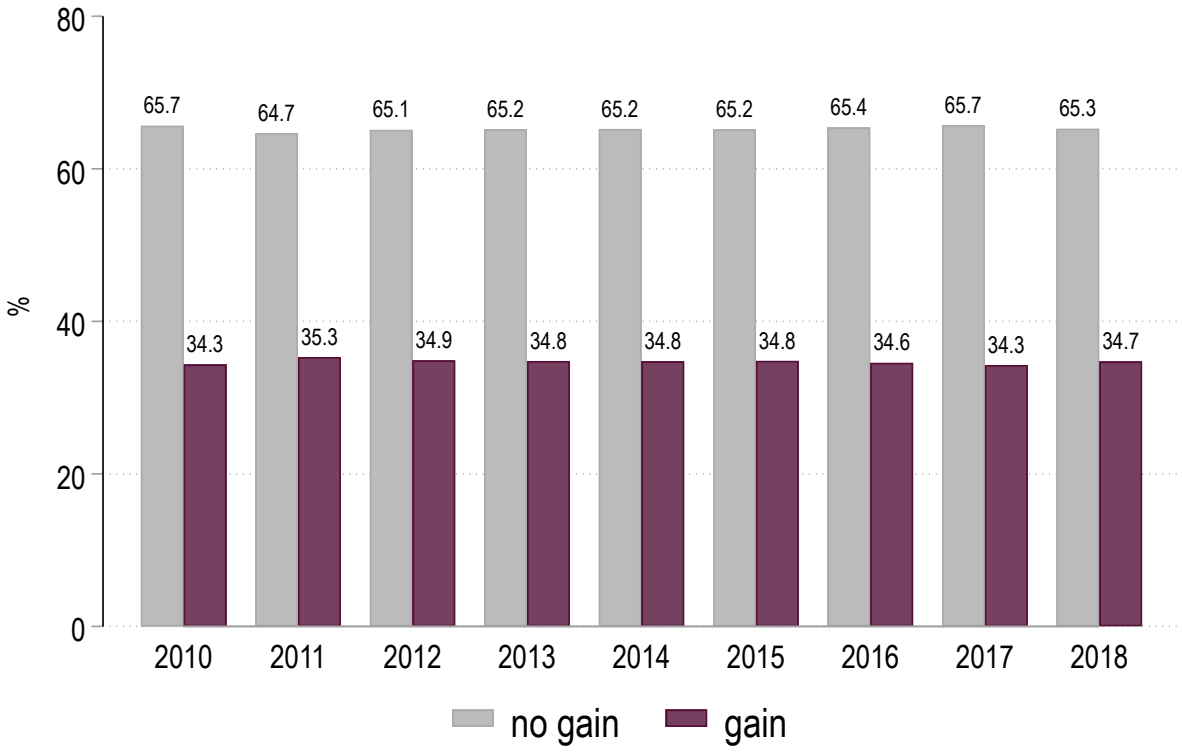
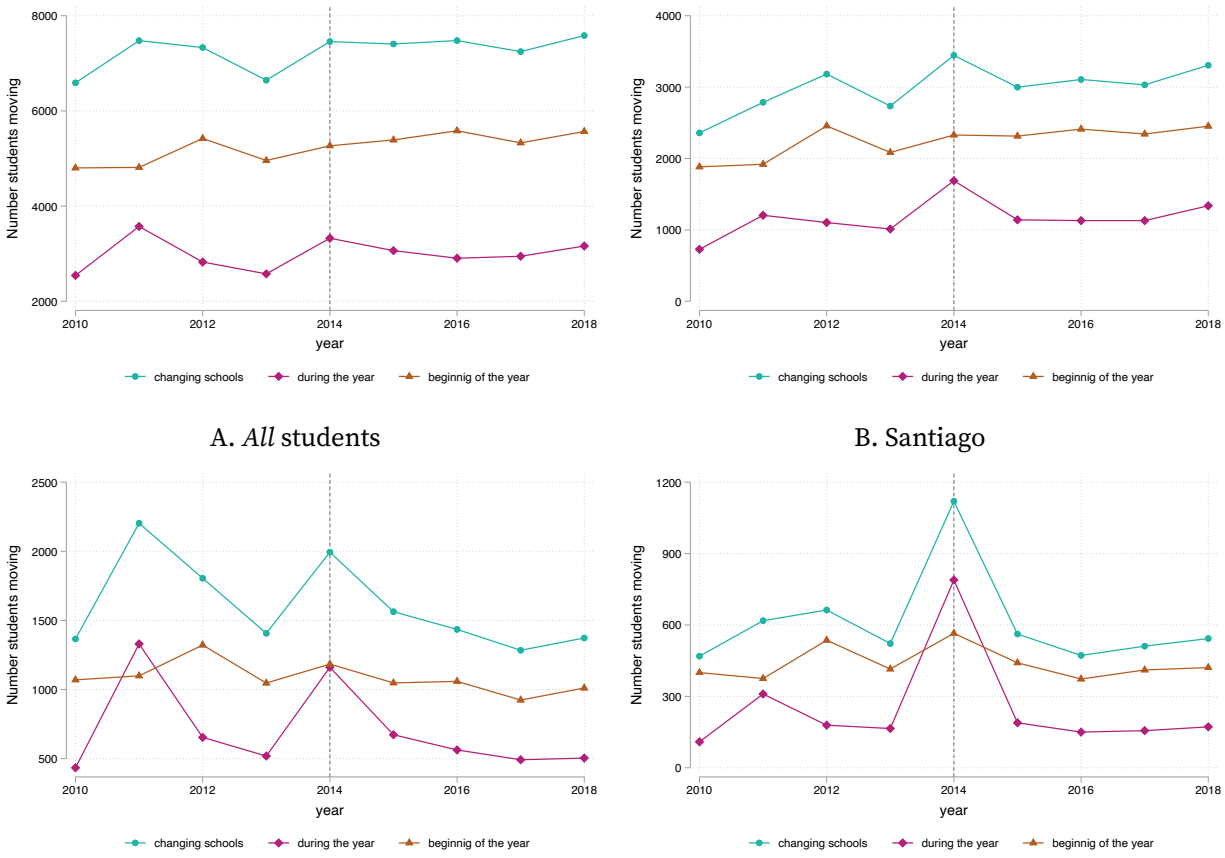


FIGURE 4. Share of Students with a Positive Potential Gain

Note: This figure presents the percentage of students with a positive potential gain (purple bars) and no potential gain (gray bars) in their choice set, defined as a 2-km buffer around their primary schools, between 2010 and 2018.

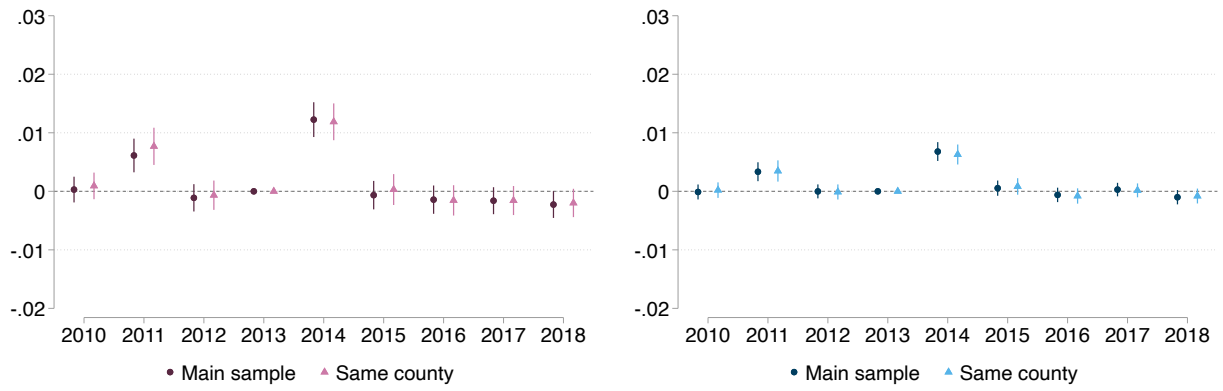


A. *All* students B. Santiago

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).

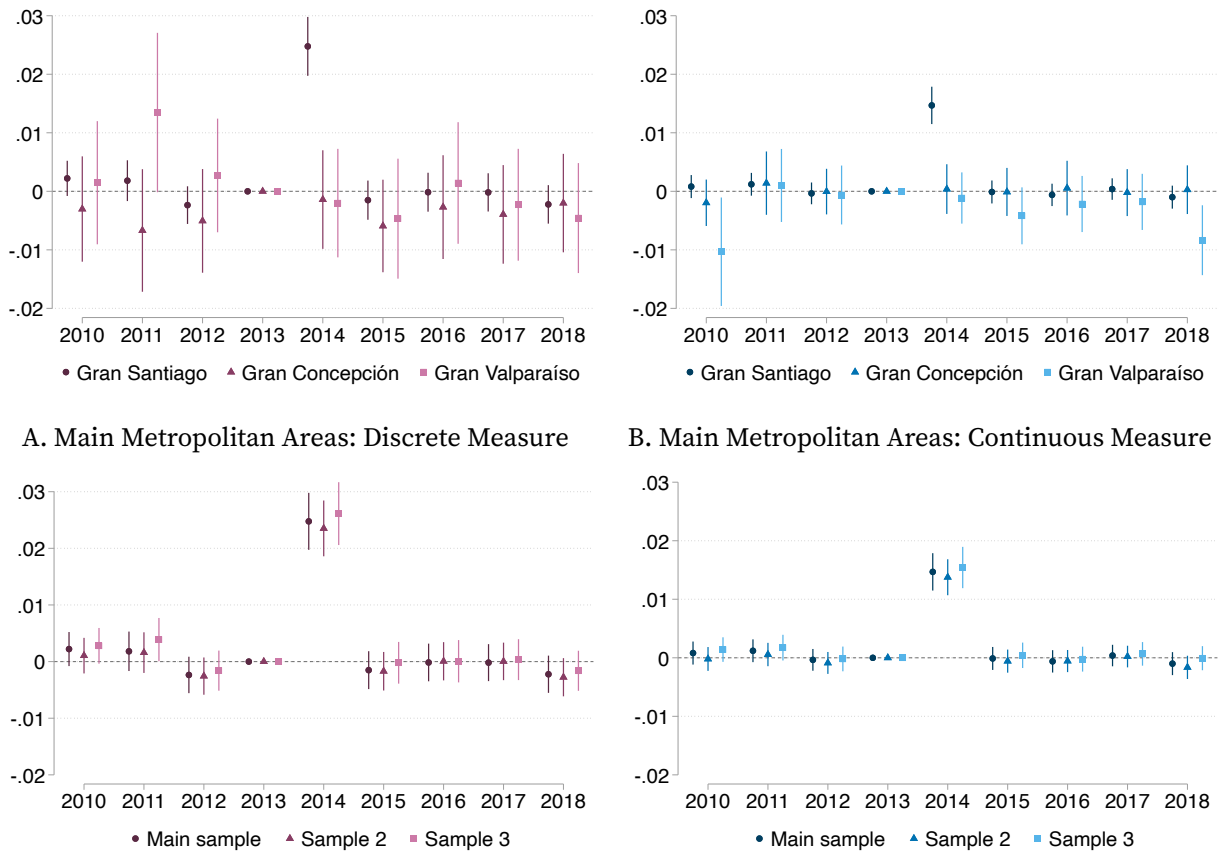


A. Discrete Measure

B. Continuous Measure

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

Note: This figure plots the coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade. In Panel A the key regressors are the interactions between an indicator for having a positive median potential gain and event year dummies. In Panel B, the main regressors are the interaction of a standardized measure of potential gain and event year dummies. Both panels include fixed effects for within-school GPA deciles. The event of interest is the release of the RR policy formula in 2014. Each panel reports two samples: the main sample, of students living in the same region during primary and secondary school, and a restricted sample of students who lived in the same county during both. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). In Panel B this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



A. Main Metropolitan Areas: Discrete Measure

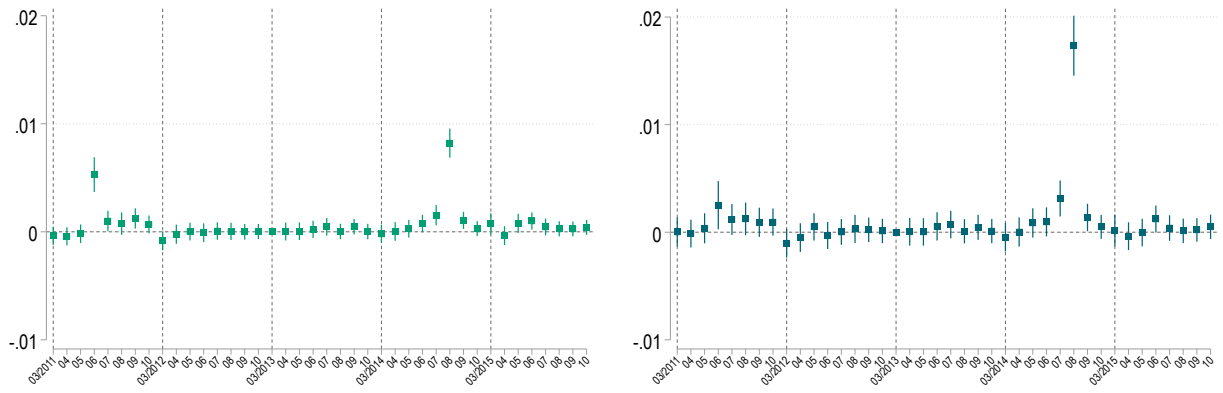
B. Main Metropolitan Areas: Continuous Measure

C. Gran Santiago: Discrete Measure

D. Gran Santiago: Continuous Measure

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

Note: This figure plots the coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade. In Panels A and C the key regressors are the interactions between an indicator for having a positive median potential gain and event year dummies. In Panels B and D, the main regressors are the interaction of a standardized measure of potential gain and event year dummies. All panels include fixed effects for within-school GPA deciles. Panels A and B are estimated separately for students living in each of the three largest metropolitan areas: Gran Santiago, Gran Concepción and Gran Valparaíso, using students who lived in the same metropolitan area during primary and secondary school. Metropolitan areas are those defined by the government under Law No. 21.074. Panels C and D use Gran Santiago only and report three samples: the main sample, of students living in Gran Santiago during primary and secondary school; a second sample of students living in Gran Santiago during primary school; and a third that additionally requires for students to live in the same county in both. The event of interest is the release of the RR policy formula in 2014. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year). In Panels B and D this is the change associated with a one standard deviation higher potential gain. 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 2014. 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.

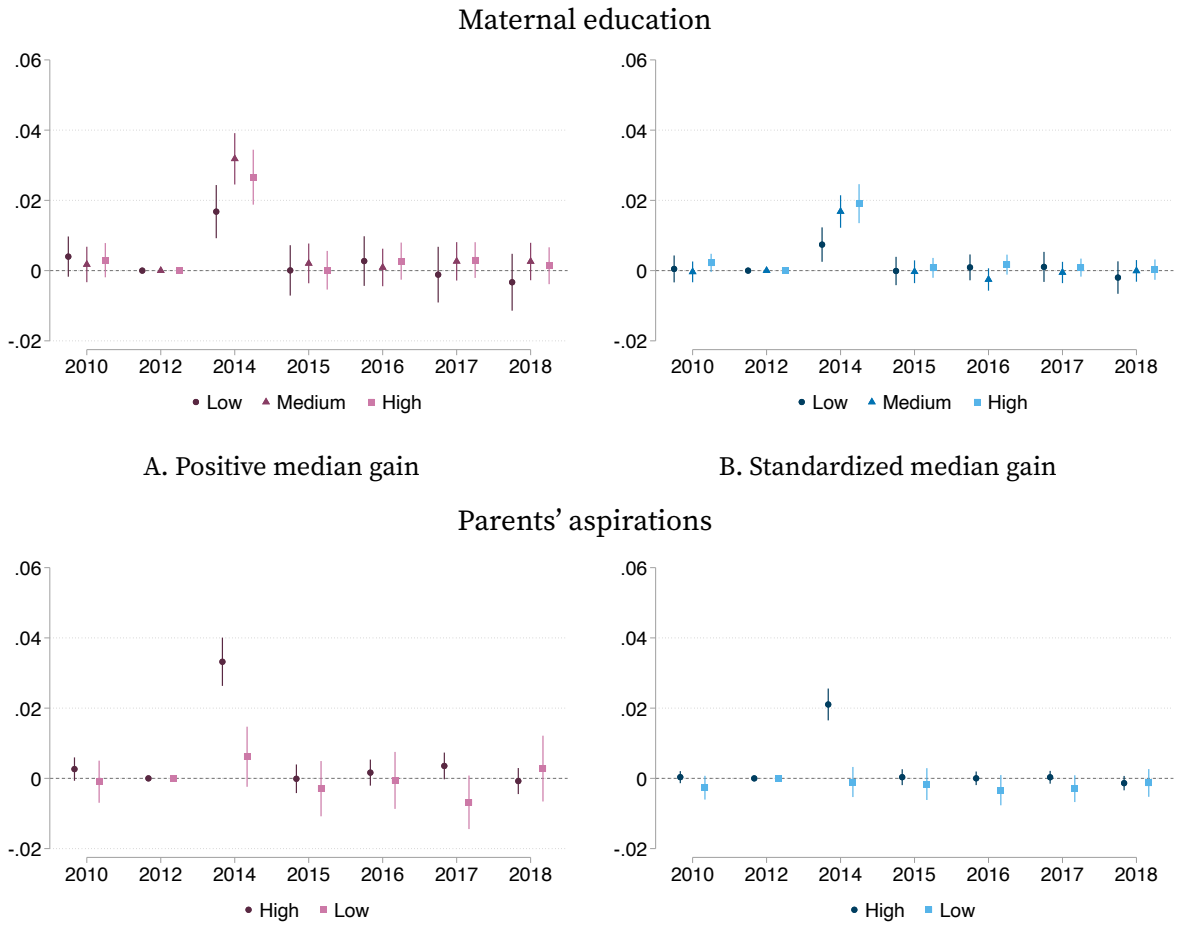


FIGURE 9. Heterogeneous Impact of the RR Policy Disclosure on School Switching, by Family Characteristics

Note: This figure plots the coefficients from estimating Equation (4) separately by group, where the outcome is an indicator for switching schools in twelfth grade. In the left figures the key regressors are the interactions between an indicator for having a positive median potential gain and event year dummies; in the right figures, the interactions between the median potential gain, standardized within the graduating cohort, and event year dummies. The first two figures present the results by the mother's education (less than secondary, secondary, more than secondary) and the last two by whether the parents expected the student to attend university. Both variables come from the parent questionnaire of the tenth-grade SIMCE test, which was not administered to the cohorts finishing twelfth grade in 2011 and 2013, so those cohorts are excluded and 2012 is the omitted year. The event of interest is the release of the RR policy formula in 2014. The sample is students living in Gran Santiago during primary and secondary school and attending a secondary school in the area. All regressions include fixed effects for within-school GPA deciles and for the school where the student starts twelfth grade. The y-axis reports the change in the probability of switching relative to 2012; in the right figures this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.

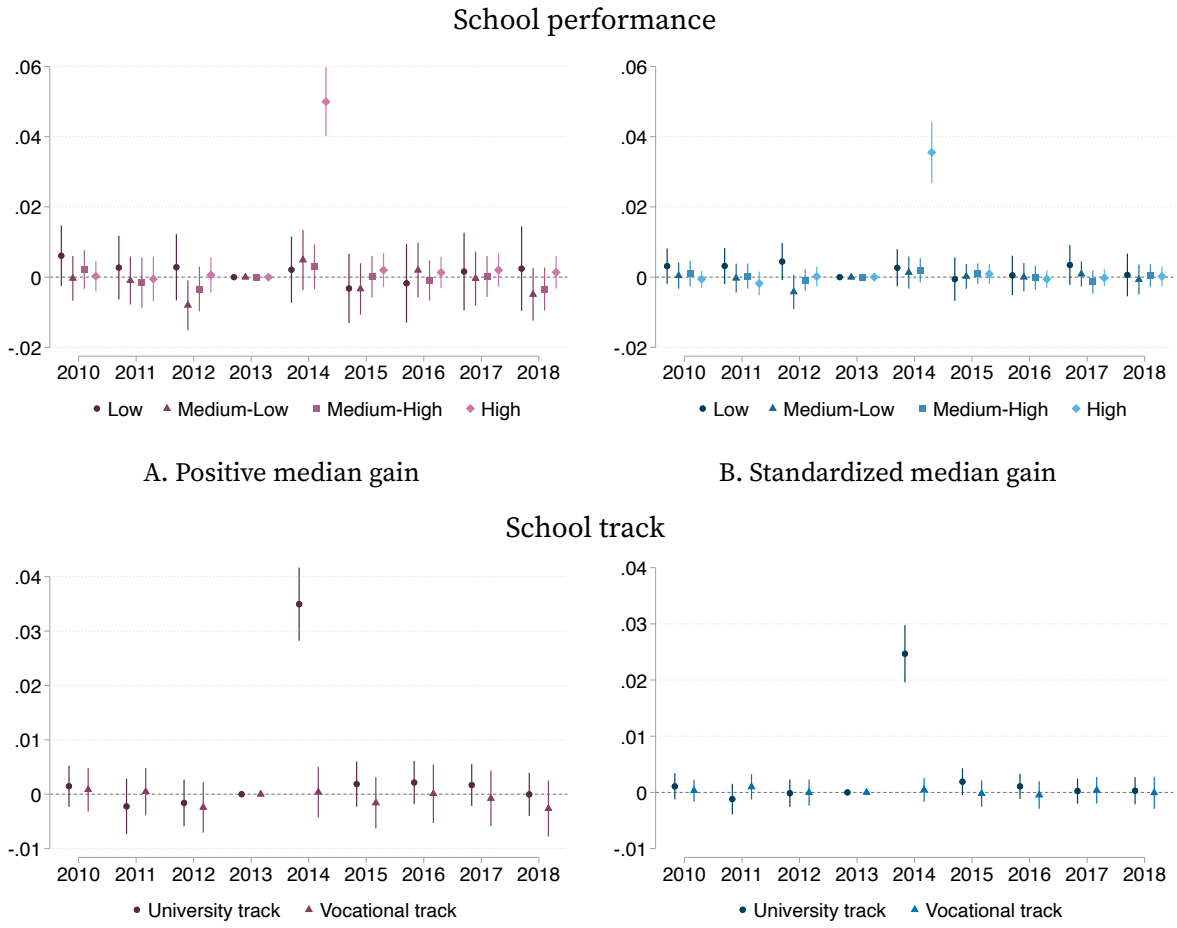
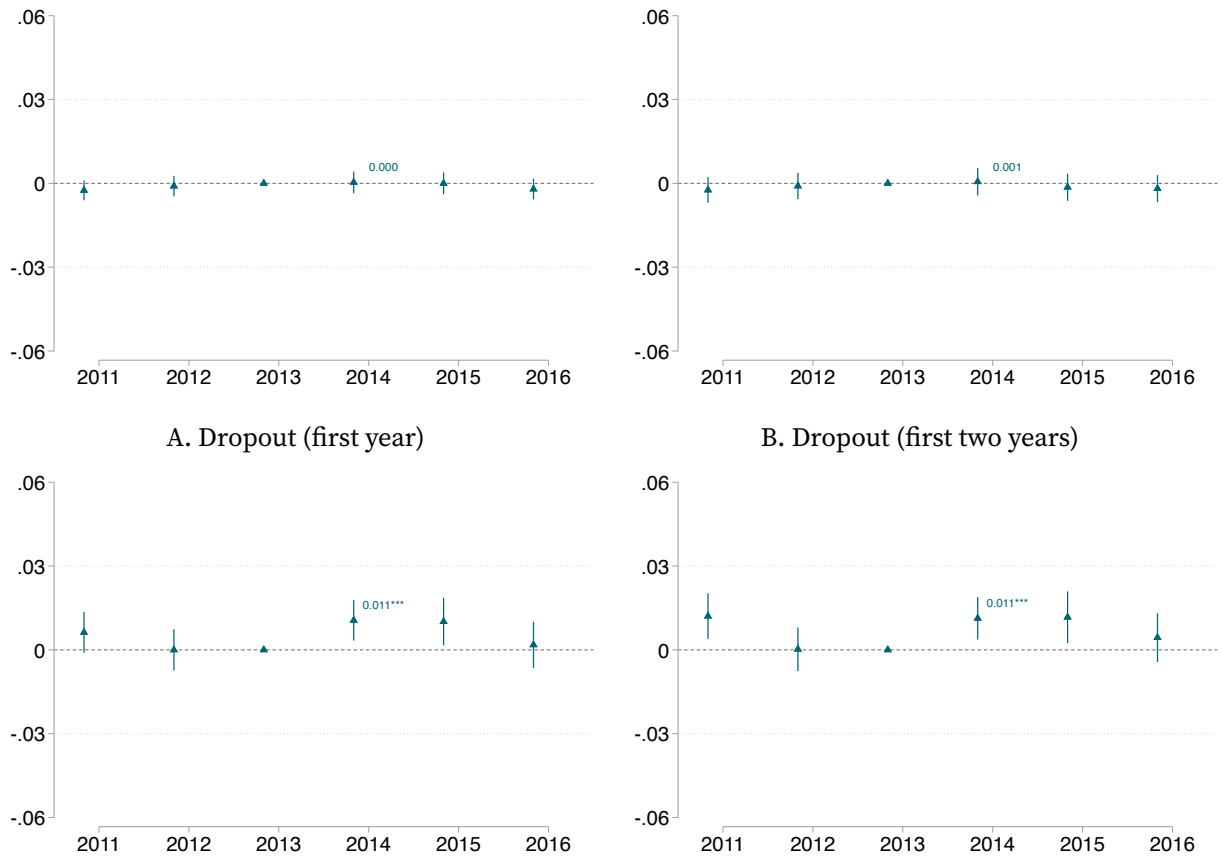


FIGURE 10. Heterogeneous Impact of the RR Policy Disclosure on School Switching, by School Characteristics

Note: This figure plots the coefficients from estimating Equation (4) separately by group, where the outcome is an indicator for switching schools in twelfth grade. In the left figures the key regressors are the interactions between an indicator for having a positive median potential gain and event year dummies; in the right figures, the interactions between the median potential gain, standardized within the graduating cohort, and event year dummies. The first two figures present the results by the school's performance quartile in the tenth-grade standardized test, measured in 2010, and the last two by school track (college-preparatory or vocational). The event of interest is the release of the RR policy formula in 2014. The sample is students living in Gran Santiago during primary and secondary school and attending a secondary school in the area, cohorts entering twelfth grade between 2010 and 2018. All regressions include fixed effects for within-school GPA deciles and for the school where the student starts twelfth grade. The y-axis reports the change in the probability of switching relative to 2013 (the omitted year); in the right figures this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



A. Dropout (first year)

B. Dropout (first two years)

C. Graduation from Tier 1–2

D. Graduation from Higly Selective Programs

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

Note: This figure plots the coefficients from estimating equation (5) 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 from tier 1–2 universities (Panel C) and graduating from 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 2014. 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% (*).

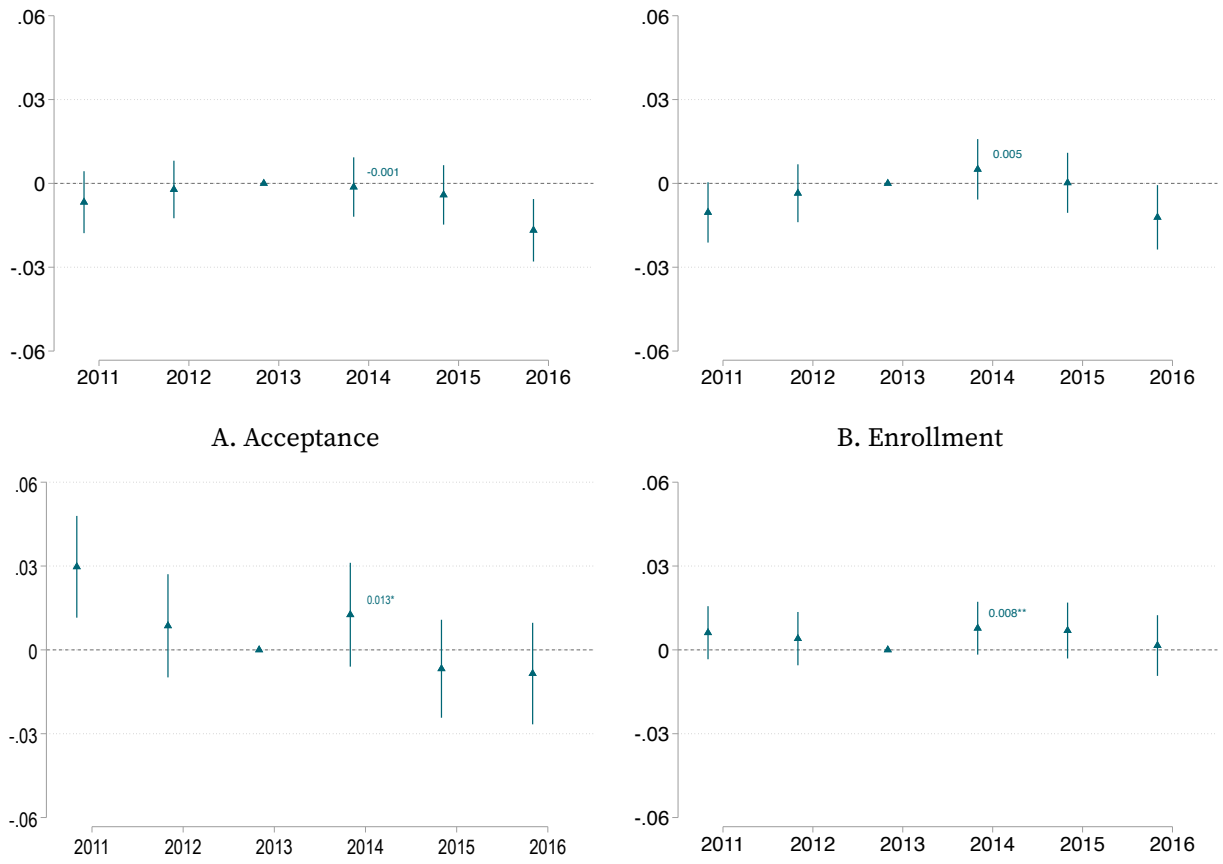
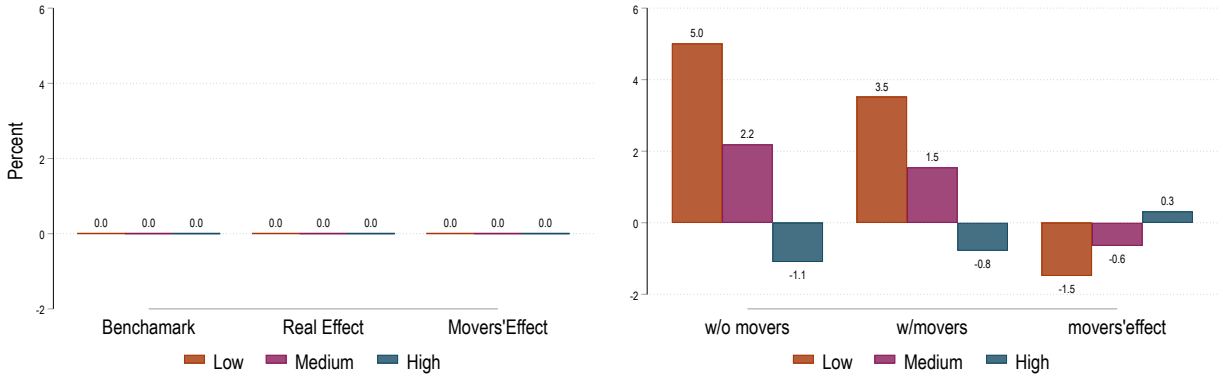


FIGURE 12. Impact of the RR Policy Disclosure on University Admission and Enrollment

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 2014. 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 13. 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. in the system	Private U. outside the system	IP	CFT
	(1)	(2)	(3)	(4)	(5)
Panel 1: *College characteristics*					
Slots	37.91	52.30	39.36	43.83	47.98
Annual tuition (in CLP)	2,197,323.16	2,846,087.19	2,072,740.48	1,237,337.38	1,185,249.22
Ratio stem degree	0.31	0.30	0.00	0.00	0.00
Ratio accredited majors	0.37	0.36	0.33	0.24	0.21
Number of programs	849	1002	1575	3185	1630
Panel 2: *Enrolled students*					
Total enrollment	39,383.00	58,612.00	47,380.00	126,572.00	65,447.00
Total female enrollment	19,208.00	28,456.00	27,432.00	62,429.00	32,979.00
Panel 3: *Application requirements' weights*					
average weight high school GPA	15.80	16.36	58.61	.	.
average weight relative ranking	26.05	18.83	38.44	.	.
average weight PSU verbal	20.69	21.22	46.96	.	.
average weight PSU quantitative	24.63	29.98	47.35	.	.

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. Submitted Preference Lists and Admission Outcomes for Academic Years 2013 and 2015

	Fraction reporting (1)	Admission rate (2)	Share of admitted (3)
Panel A. *Admission year 2013*			
Choice 1	1.000	0.429	0.532
Choice 2	0.933	0.196	0.227
Choice 3	0.831	0.123	0.126
Choice 4	0.627	0.069	0.054
Choice 5	0.454	0.051	0.029
Choice 6	0.316	0.038	0.015
Choice 7	0.221	0.030	0.008
Choice 8	0.156	0.022	0.004
Choice 9	0.106	0.019	0.003
Choice 10	0.078	0.016	0.002
Nb. applicants / admitted	118,208		95,300
Panel B. *Admission year 2015*			
Choice 1	1.000	0.413	0.532
Choice 2	0.929	0.189	0.226
Choice 3	0.819	0.117	0.123
Choice 4	0.606	0.073	0.057
Choice 5	0.436	0.057	0.032
Choice 6	0.302	0.042	0.016
Choice 7	0.207	0.025	0.007
Choice 8	0.145	0.019	0.004
Choice 9	0.099	0.019	0.002
Choice 10	0.070	0.015	0.001
Nb. applicants / admitted	125,588		97,620

Note: This table reports application and admission outcomes for Chilean college applicants, by preference rank. Column (1) reports the share of all applicants who list at least k preferences. Column (2) reports the share admitted at preference k among applicants who listed a k-th preference; denominators therefore differ across rows and entries are not additive. Column (3) reports the distribution of admitted students across the preference at which they were placed, and sums to one. Panel A covers admission year 2013, first cohort applying under the Relative Ranking policy. Panel B covers admission year 2015, the cohort underlying the counterfactual simulations in Section 7.

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

TABLE A4. Selectivity by Institution, 2012 Admission Process

University	Mean	Std. Dev.	P10	P25	P50	P75	P90	Admitted	Tier
UCH	691.56	46.09	630.90	658.25	688.90	723.55	751.90	5,424	1
PUC	694.75	52.53	630.60	652.80	690.40	734.20	769.90	4,754	1
USACH	633.90	36.64	591.80	610.70	631.75	654.90	676.60	4,725	2
UAI	656.25	37.10	610.30	633.70	655.55	678.30	702.30	1,868	2
UANDE	657.23	53.55	586.00	613.60	657.60	694.90	723.90	1,221	2
UDEC	602.88	62.86	521.30	554.30	601.85	645.05	687.45	6,377	3
UTFSM	615.26	78.90	506.90	547.70	629.20	680.50	708.20	4,346	3
UV	596.58	54.47	532.70	558.70	589.88	625.30	671.50	3,984	3
PUCV	610.95	43.06	557.40	581.40	608.30	637.70	667.30	3,448	3
UACH	582.65	58.14	514.55	541.60	577.15	617.02	660.40	3,076	3
UDD	605.96	55.06	537.85	566.20	603.00	636.10	673.90	2,903	3
UDP	617.22	40.02	571.20	590.00	613.33	638.85	668.60	2,726	3
UFRO	592.74	56.16	525.10	549.90	586.30	627.10	669.20	2,354	3
UCN	589.36	55.32	520.40	546.35	583.60	625.10	664.80	2,322	3
UTAL	616.17	52.12	551.40	582.92	615.02	646.90	685.90	1,904	3
UCM	581.56	48.03	527.80	546.10	573.25	606.75	644.30	1,639	3
UAH	595.67	38.86	547.40	567.50	593.90	619.60	646.80	1,539	3
UFT	580.95	59.61	509.70	540.85	575.70	613.70	660.05	1,145	3
UMCE	605.76	33.62	570.00	580.77	603.33	624.95	649.05	1,092	3
UNAB	550.38	53.70	484.50	511.90	546.80	583.70	618.60	12,615	4
UMAYO	571.86	56.56	501.40	529.00	568.00	604.40	645.80	4,895	4
UCSC	563.23	51.92	502.75	525.60	557.60	593.40	625.45	2,451	4
UBB	577.58	43.70	523.40	544.50	572.45	604.35	639.70	2,449	4
UTEM	548.76	36.01	503.20	524.55	548.35	574.25	595.05	2,392	4
UCT	543.95	43.09	492.05	509.60	540.05	571.35	598.80	2,206	4
ULS	575.44	45.06	521.40	542.50	569.40	605.70	635.40	1,791	4
UPA	556.07	37.49	512.05	530.03	553.02	578.55	604.00	1,748	4
UTA	557.07	51.94	493.70	517.17	549.02	594.40	627.80	1,720	4
UANT	566.13	65.25	487.20	515.70	558.30	606.70	662.15	1,433	4
UNAP	550.89	47.10	493.80	514.08	541.30	583.88	616.45	928	4
UDA	550.61	50.05	486.85	511.90	549.50	585.70	616.60	815	4
ULAG	541.04	44.78	484.40	508.20	535.80	571.00	603.75	785	4
UMAG	554.09	50.70	492.10	516.15	547.45	586.00	626.05	499	4

Note: This table reproduces Kapor, Karnani, and Neilson (2024) Table A-2 that presents the distribution of admission scores among students admitted through the centralized system in the 2012 admission process, for each participating university. Universities are grouped into tiers. Tier 1 as universities with an average admitted score in $[660, 700)$, tier 2 in $[620, 660)$, tier 3 in $[580, 620)$ and tier 4 in $[540, 580)$. Within each tier, universities are ordered by the number of students they admitted. The 2012 process includes eight private universities that joined the platform that year, the number of universities in the centralized system stay estable until 2017 process.

TABLE A5. Alternative Specifications: Discrete Measure of Potential Gain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Positive gain × 2010	0.0022*	0.0022*	0.0014	0.0026**	0.0010	0.0013	0.0002	0.0009	0.0013	0.0003
	(0.0012)	(0.0012)	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0016)	(0.0022)
Positive gain × 2011	0.0019	0.0019	0.0025	0.0011	-0.0008	-0.0001	-0.0011	-0.0007	-0.0026	-0.0030
	(0.0013)	(0.0013)	(0.0016)	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0018)	(0.0025)
Positive gain × 2012	-0.0020	-0.0020	-0.0020	-0.0018	-0.0022	-0.0019	-0.0022	-0.0034**	-0.0034*	-0.0066***
	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0023)
Positive gain × 2013	[base]	[base]	[base]	[base]	[base]	[base]	[base]	[base]	[base]	[base]
Positive gain × 2014	0.0250***	0.0250***	0.0287***	0.0274***	0.0222***	0.0209***	0.0159***	0.0056***	0.0043**	-0.0006
	(0.0020)	(0.0020)	(0.0022)	(0.0022)	(0.0021)	(0.0021)	(0.0020)	(0.0017)	(0.0019)	(0.0025)
Positive gain × 2015	-0.0014	-0.0014	-0.0018	-0.0014	-0.0010	-0.0001	-0.0009	-0.0012	-0.0012	-0.0020
	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0024)
Positive gain × 2016	-0.0004	-0.0004	-0.0010	-0.0008	-0.0002	0.0008	0.0005	0.0014	0.0008	0.0020
	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0025)
Positive gain × 2017	-0.0002	-0.0001	-0.0005	0.0009	0.0010	0.0024	0.0013	-0.0008	0.0007	0.0013
	(0.0013)	(0.0013)	(0.0015)	(0.0014)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0024)
Positive gain × 2018	-0.0020	-0.0020	-0.0022	-0.0010	0.0004	0.0020	0.0005	-0.0023	-0.0007	-0.0010
	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0019)	(0.0024)
School FE	✓	✓	✓	✓	✓	✓	✓			
GPA decile FE	✓	✓	✓					✓		
Market size		✓								
Market × year FE			✓							
Decile × year FE				✓	✓	✓	✓		✓	
Baseline threshold × year					✓	✓				
Baseline SIMCE × year						✓				
Contemporaneous threshold × year							✓			
School × year FE								✓	✓	
School × decile × year FE										✓
Observations	577,022	577,022	576,239	577,022	539,794	495,754	577,022	576,999	576,999	568,830

Note: This table reports the coefficients from estimating equation (4) under alternative sets of controls and fixed effects. 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. Each column's controls and fixed effects are shown in the lower panel. Column (1) is the specification used throughout the paper, with fixed effects for the school attended at the start of twelfth grade and for within-school GPA deciles. Columns (2) and (3) each add one term to it: the number of schools in the student's market, and market × year fixed effects. Column (4) replaces the decile fixed effects with decile × year. Columns (5) and (6) add to column (4) the school's baseline threshold and then its baseline SIMCE score, each interacted with year, and column (7) instead adds the school's contemporaneous threshold interacted with year. Column (8) absorbs school × year together with decile fixed effects, and column (9) with decile × year. Column (10) absorbs school × decile × year. Because columns (8) to (10) absorb the school interacted with year, they subsume the school main effect, and column (10) likewise subsumes the decile. The sample is students living in Gran Santiago in both primary and secondary school who attend a school located in Gran Santiago. Standard errors, in parentheses, are clustered at the students' market level and 2013 is the omitted year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A6. Alternative Specifications: Continuous Measure of Potential Gain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Potential gain × 2010	0.0009	0.0009	0.0006	0.0009	0.0003	0.0004	-0.0003	-0.0006	-0.0006	-0.0010
	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0014)
Potential gain × 2011	0.0012	0.0012	0.0019**	0.0011	0.0004	0.0008	0.0001	-0.0010	-0.0013	-0.0005
	(0.0007)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0010)	(0.0010)	(0.0016)
Potential gain × 2012	-0.0002	-0.0002	0.0003	-0.0002	-0.0000	-0.0000	-0.0002	-0.0007	-0.0007	-0.0022
	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0016)
Potential gain × 2013	[base]	[base]	[base]	[base]	[base]	[base]	[base]	[base]	[base]	[base]
Potential gain × 2014	0.0150***	0.0150***	0.0178***	0.0149***	0.0146***	0.0150***	0.0100***	0.0020*	0.0015	-0.0003
	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0012)	(0.0011)	(0.0011)	(0.0018)
Potential gain × 2015	-0.0000	-0.0000	0.0000	-0.0000	0.0004	0.0005	0.0004	-0.0003	-0.0003	-0.0012
	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0016)
Potential gain × 2016	-0.0006	-0.0006	-0.0008	-0.0007	-0.0002	-0.0001	-0.0003	-0.0005	-0.0007	-0.0001
	(0.0007)	(0.0007)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0015)
Potential gain × 2017	0.0004	0.0004	0.0005	0.0004	0.0004	0.0005	0.0004	-0.0007	-0.0007	-0.0015
	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0014)
Potential gain × 2018	-0.0009	-0.0009	-0.0008	-0.0009	0.0003	0.0009	-0.0004	-0.0014	-0.0013	0.0001
	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0010)	(0.0010)	(0.0015)
School FE	✓	✓	✓	✓	✓	✓	✓			
GPA decile FE	✓	✓	✓					✓		
Market size		✓								
Market × year FE			✓							
Decile × year FE				✓	✓	✓	✓		✓	
Baseline threshold × year					✓	✓				
Baseline SIMCE × year						✓				
Contemporaneous threshold × year							✓			
School × year FE								✓	✓	
School × decile × year FE										✓
Observations	577,022	577,022	576,239	577,022	539,794	495,754	577,022	576,999	576,999	568,830

Note: This table reports the coefficients from estimating equation (4) under alternative sets of controls and fixed effects. The outcome is an indicator for switching schools in twelfth grade and the key regressors are the interactions between the student's median potential gain, standardized within their graduating cohort, and event-year dummies. Coefficients are therefore the change in the probability of switching associated with a one standard deviation higher potential gain. Each column's controls and fixed effects are shown in the lower panel. Column (1) is the specification used throughout the paper, with fixed effects for the school attended at the start of twelfth grade and for within-school GPA deciles. Columns (2) and (3) each add one term to it: the number of schools in the student's market, and market × year fixed effects. Column (4) replaces the decile fixed effects with decile × year. Columns (5) and (6) add to column (4) the school's baseline threshold and then its baseline SIMCE score, each interacted with year, and column (7) instead adds the school's contemporaneous threshold interacted with year. Column (8) absorbs school × year together with decile fixed effects, and column (9) with decile × year. Column (10) absorbs school × decile × year. Because columns (8) to (10) absorb the school interacted with year, they subsume the school main effect, and column (10) likewise subsumes the decile. The sample is students living in Gran Santiago in both primary and secondary school who attend a school located in Gran Santiago. Standard errors, in parentheses, are clustered at the students' market level and 2013 is the omitted year. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

TABLE A7. Shapley Decomposition of the Variance of the Potential Gain

	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Panel A. Positive median gain (discrete measure)										
GPA decile within own school	11.0	11.7	11.4	11.6	12.5	12.0	11.5	11.6	11.8	11.7
Own school threshold	15.2	15.6	16.0	16.9	17.2	18.1	18.4	18.3	18.4	17.0
Market structure	13.4	12.4	12.6	11.2	9.9	10.4	10.3	9.3	8.7	10.6
GPA decile × own school threshold	23.5	22.8	22.7	22.5	23.0	22.7	22.2	22.5	22.6	22.9
GPA decile × market structure	8.1	8.0	7.8	7.7	7.9	7.4	7.3	7.3	7.2	7.8
Own school threshold × market structure	9.9	10.5	10.7	11.2	10.9	11.3	12.1	12.3	12.5	11.3
GPA decile × own school threshold × market structure	19.0	19.0	18.9	18.9	18.4	18.1	18.3	18.6	18.8	18.7
R-squared	0.496	0.488	0.496	0.492	0.513	0.499	0.492	0.498	0.494	0.490
Panel B. Median potential gain (continuous measure)										
GPA decile within own school	6.3	6.0	6.2	6.0	6.1	6.9	6.6	6.8	7.3	6.4
Own school threshold	18.8	18.6	19.3	19.6	19.9	20.7	20.2	20.0	20.4	19.6
Market structure	7.4	7.7	7.7	7.9	7.9	7.2	7.2	6.9	7.0	7.3
GPA decile × own school threshold	26.0	26.1	25.5	24.8	25.9	25.0	24.4	24.1	23.7	25.1
GPA decile × market structure	12.1	11.6	10.5	10.5	10.1	9.7	10.3	10.1	10.3	10.9
Own school threshold × market structure	11.1	11.6	12.1	12.5	11.9	12.6	13.1	13.6	13.5	12.5
GPA decile × own school threshold × market structure	18.3	18.4	18.6	18.7	18.1	17.9	18.1	18.4	17.8	18.4
R-squared	0.526	0.540	0.567	0.578	0.605	0.576	0.562	0.563	0.555	0.557

Note: This table decomposes the variance of the potential gain separately for each graduating cohort using the Shapley decomposition method. The potential gain is a function of the student's GPA, the admission threshold of the school they start twelfth grade in, and the structure of the school market around them. Each row reports the share of the explained variation attributable to one input or to an interaction between them, and the shares sum to 100 in every column. Panel A decomposes the indicator for a positive median gain and Panel B the median gain standardized within the graduating cohort. The last column pools all cohorts. Terms involving the origin school's threshold account for 69.9% of the explained variation in Panel A and 75.6% in Panel B, and their share moves smoothly across cohorts with no break in 2014.

TABLE A8. Event Study for Destination School Outcomes Using the Positive Median Gain

	(1) Lower threshold	(2) Lower mean PSU	(3) Lower boundness	(4) Lower boundness (Tier 1)	(5) Lower performance	(6) Lower economic group	(7) Closer school
Positive gain × 2010	-0.0050***	-0.0032**	-0.0056***	-0.0034**	-0.0038***	-0.0018	-0.0009
	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0011)	(0.0011)	(0.0012)
Positive gain × 2011	-0.0009	-0.0001	0.0003	0.0003	0.0007	0.0016	-0.0006
	(0.0016)	(0.0017)	(0.0015)	(0.0016)	(0.0013)	(0.0012)	(0.0013)
Positive gain × 2012	-0.0008	-0.0010	-0.0007	0.0009	-0.0014	-0.0010	-0.0006
	(0.0016)	(0.0017)	(0.0016)	(0.0015)	(0.0013)	(0.0012)	(0.0013)
Positive gain × 2013	[base]	[base]	[base]	[base]	[base]	[base]	[base]
Positive gain × 2014	0.0238***	0.0250***	0.0237***	0.0248***	0.0190***	0.0211***	0.0112***
	(0.0022)	(0.0023)	(0.0022)	(0.0022)	(0.0018)	(0.0018)	(0.0017)
Positive gain × 2015	-0.0005	-0.0006	-0.0009	0.0000	-0.0004	0.0005	-0.0031**
	(0.0015)	(0.0016)	(0.0015)	(0.0014)	(0.0011)	(0.0012)	(0.0013)
Positive gain × 2016	-0.0011	-0.0025	-0.0010	-0.0006	0.0002	-0.0010	-0.0012
	(0.0016)	(0.0017)	(0.0015)	(0.0014)	(0.0012)	(0.0012)	(0.0013)
Positive gain × 2017	-0.0025	-0.0029*	-0.0027*	-0.0028**	-0.0008	-0.0003	-0.0022*
	(0.0015)	(0.0016)	(0.0014)	(0.0013)	(0.0011)	(0.0011)	(0.0013)
Positive gain × 2018	-0.0027*	-0.0003	-0.0010	-0.0006	-0.0005	0.0006	-0.0023*
	(0.0015)	(0.0017)	(0.0015)	(0.0014)	(0.0011)	(0.0012)	(0.0013)
Pre-policy mean	0.0205	0.0232	0.0191	0.0180	0.0115	0.0101	0.0143
Observations	576,021	557,147	547,833	547,833	511,716	511,716	573,959

Note: This table reports the coefficients from estimating Equation (4) using outcomes related to the characteristics of the destination school. Each column is a separate regression whose dependent variable is an indicator equal to one if the student switched schools in twelfth grade to a school with the characteristic in the column header relative to the school of origin, and zero otherwise, including for students who did not switch. Rows report the interactions between an indicator for having a positive median potential gain and event year dummies, relative to 2013 (the omitted year). All regressions include fixed effects for within-school GPA deciles. The event of interest is the release of the RR policy formula in 2014. The sample is students living in Gran Santiago during primary and secondary school and attending a secondary school in the area. The pre-policy mean is the mean of the outcome over the 2010–2013 cohorts. Standard errors, clustered at the school-market level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A9. Event Study for Destination School Outcomes Using the Standardized Median Gain

	(1) Lower threshold	(2) Lower mean PSU	(3) Lower boundness	(4) Lower boundness (Tier 1)	(5) Lower performance	(6) Lower economic group	(7) Closer school
Potential gain × 2010	-0.0019***	-0.0002	-0.0023***	-0.0009	-0.0016***	-0.0005	-0.0002
	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0008)
Potential gain × 2011	-0.0001	0.0007	0.0003	-0.0001	0.0004	0.0012**	-0.0001
	(0.0007)	(0.0009)	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0008)
Potential gain × 2012	-0.0002	-0.0005	0.0004	0.0007	-0.0008	-0.0000	0.0007
	(0.0007)	(0.0009)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0008)
Potential gain × 2013	[base]	[base]	[base]	[base]	[base]	[base]	[base]
Potential gain × 2014	0.0155***	0.0165***	0.0167***	0.0171***	0.0137***	0.0153***	0.0089***
	(0.0013)	(0.0015)	(0.0014)	(0.0014)	(0.0012)	(0.0012)	(0.0011)
Potential gain × 2015	0.0001	-0.0007	-0.0003	0.0001	-0.0003	0.0007	-0.0004
	(0.0007)	(0.0009)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0008)
Potential gain × 2016	-0.0009	-0.0016*	-0.0007	0.0001	-0.0006	-0.0007	-0.0004
	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0008)
Potential gain × 2017	-0.0013**	-0.0015*	-0.0018***	-0.0016**	-0.0015***	-0.0010*	-0.0003
	(0.0007)	(0.0008)	(0.0007)	(0.0006)	(0.0005)	(0.0006)	(0.0008)
Potential gain × 2018	-0.0013*	-0.0004	-0.0008	-0.0005	-0.0005	0.0000	0.0003
	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0007)
Pre-policy mean	0.0205	0.0232	0.0191	0.0180	0.0115	0.0101	0.0143
Observations	576,021	557,147	547,833	547,833	511,716	511,716	573,959

Note: This table reports the coefficients from estimating Equation (4) using outcomes related to the characteristics of the destination school. Each column is a separate regression whose dependent variable is an indicator equal to one if the student switched schools in twelfth grade to a school with the characteristic in the column header relative to the school of origin, and zero otherwise, including for students who did not switch. Rows report the interactions between a standardized measure of potential gain and event year dummies, relative to 2013 (the omitted year), so each coefficient is the change associated with a one standard deviation higher potential gain. All regressions include fixed effects for within-school GPA deciles. The event of interest is the release of the RR policy formula in 2014. The sample is students living in Gran Santiago during primary and secondary school and attending a secondary school in the area. The pre-policy mean is the mean of the outcome over the 2010–2013 cohorts. Standard errors, clustered at the school-market level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

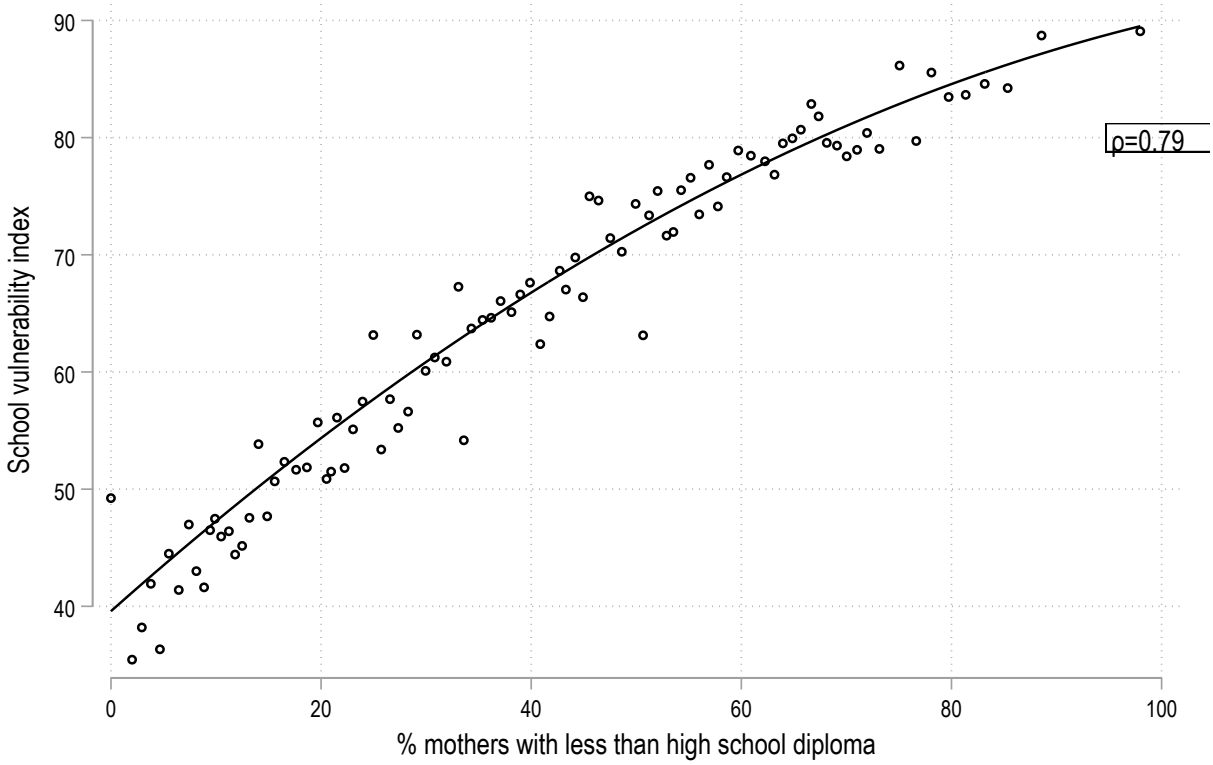


FIGURE A1. School vulnerability index & students SES

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.

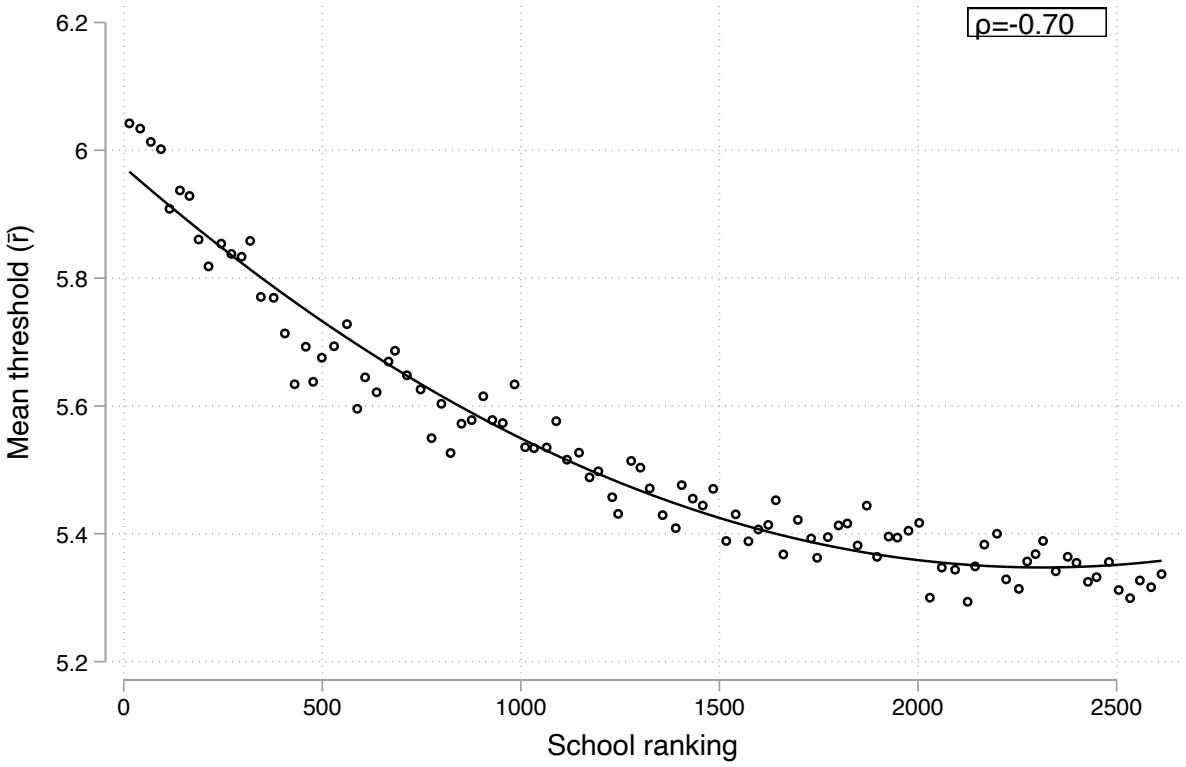


FIGURE A2. School Mean Threshold & School Ranking

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.

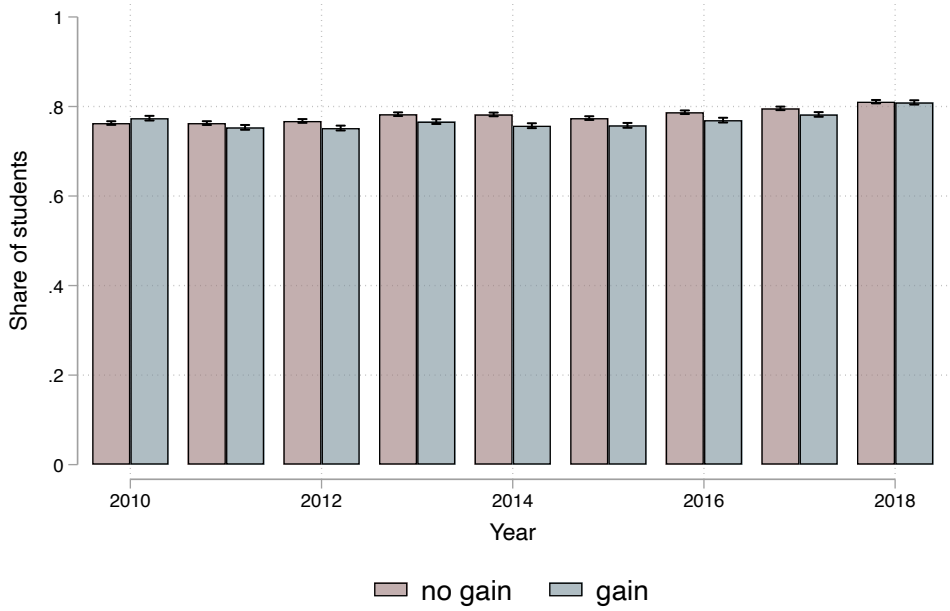
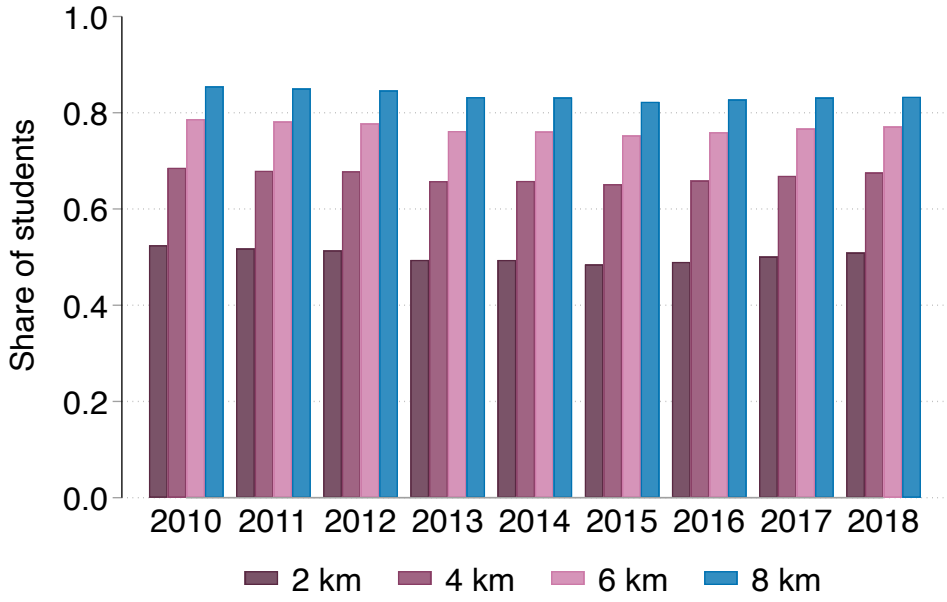
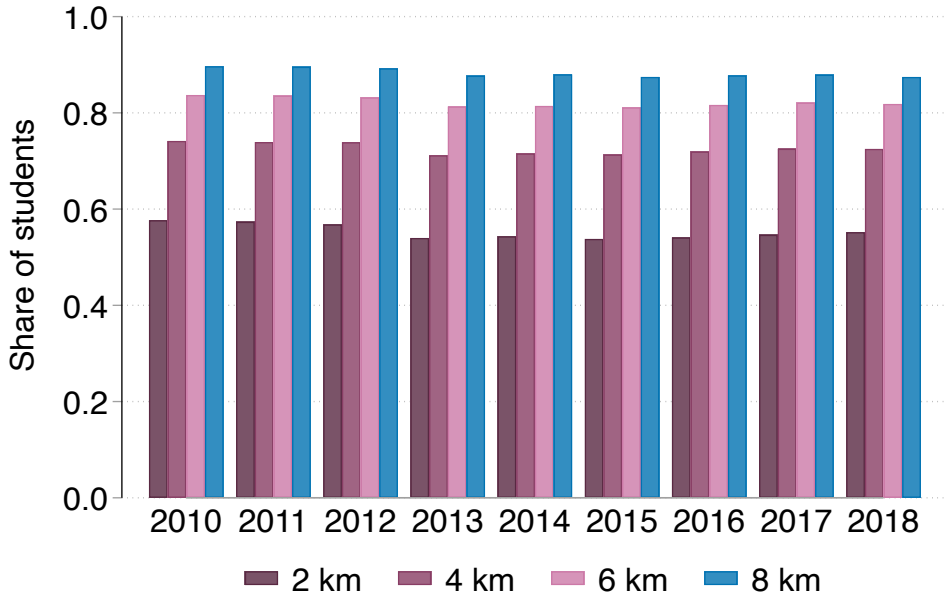


FIGURE A3. Share of Students Living in the Same County During Primary and Secondary School, Gran Santiago

Note: This figure presents the share of students living in the same county during primary school and secondary school, for each cohort starting twelfth grade between 2010 and 2018, separately for students with and without a positive median potential gain. Primary school location is calculated using the grade in which the student is first observed, while secondary school location is measured in grade twelve. The sample is students living in Gran Santiago during primary and secondary school and attending a secondary school in the area. Each bar represents the yearly share, and vertical lines indicate 95% confidence intervals.



A. Main sample



B. Same county in primary and secondary school

FIGURE A4. Distance Between the Primary School and the Twelfth-Grade School, Gran Santiago

Note: This figure presents, for each cohort starting twelfth grade between 2010 and 2018, the share of students whose twelfth-grade school lies within 2, 4, 6 and 8 km of their primary school. Distances are straight-line distances between the geolocations of the two schools; the primary school is the one in which the student is first observed. Panel A uses the main Gran Santiago sample, students living in Gran Santiago during primary and secondary school and attending a secondary school in the area. Panel B restricts it to students living in the same county in both periods.

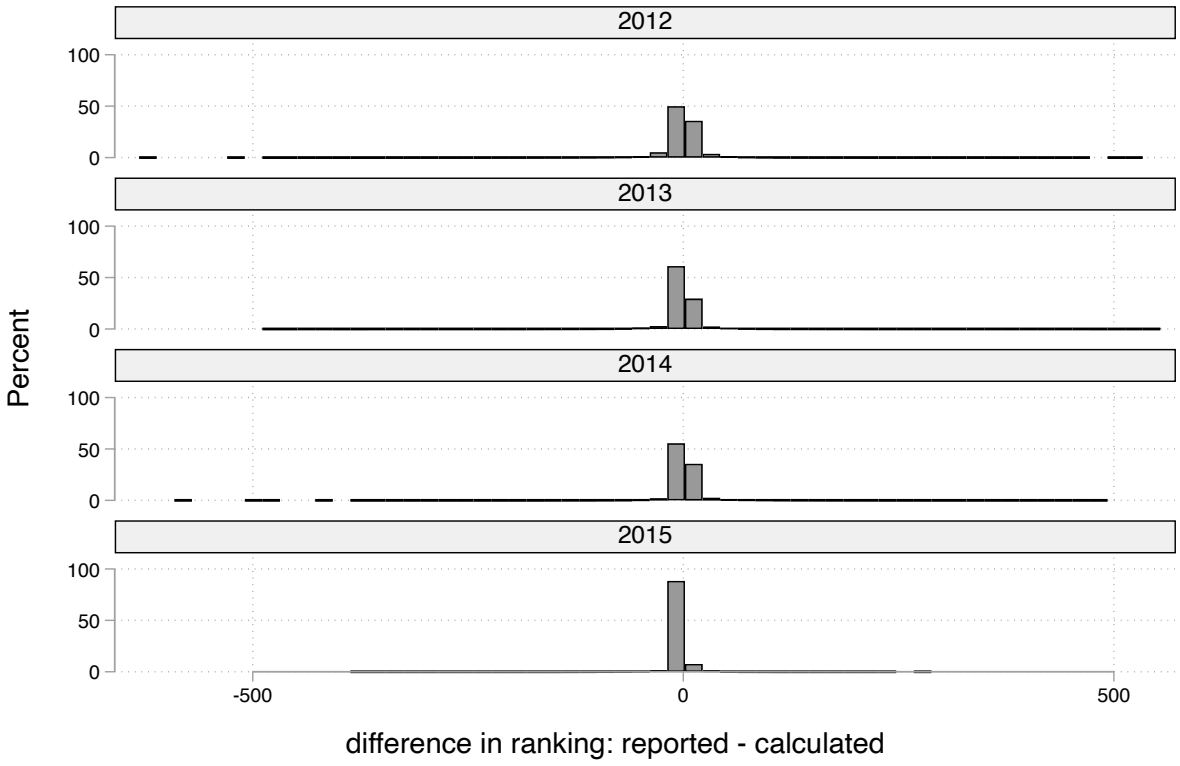


FIGURE A5. Difference between Reported Ranking Score and Calculated Ranking Score

Note: This figure plots, for each graduating cohort from 2012 to 2015, the distribution of the difference between the ranking score reported by DEMRE and the one computed with the formula described in Section 2.3, in points of the 208–850 scale used to standardized all the components in the centralized admission. The sample is students who graduated from high school and sat the PSU the following year, with the official score reported for their school of graduation. The constructed score uses the school-track threshold built from the three previous graduating cohorts and the official GPA conversion table for the student's track. Bins are 20 points wide.

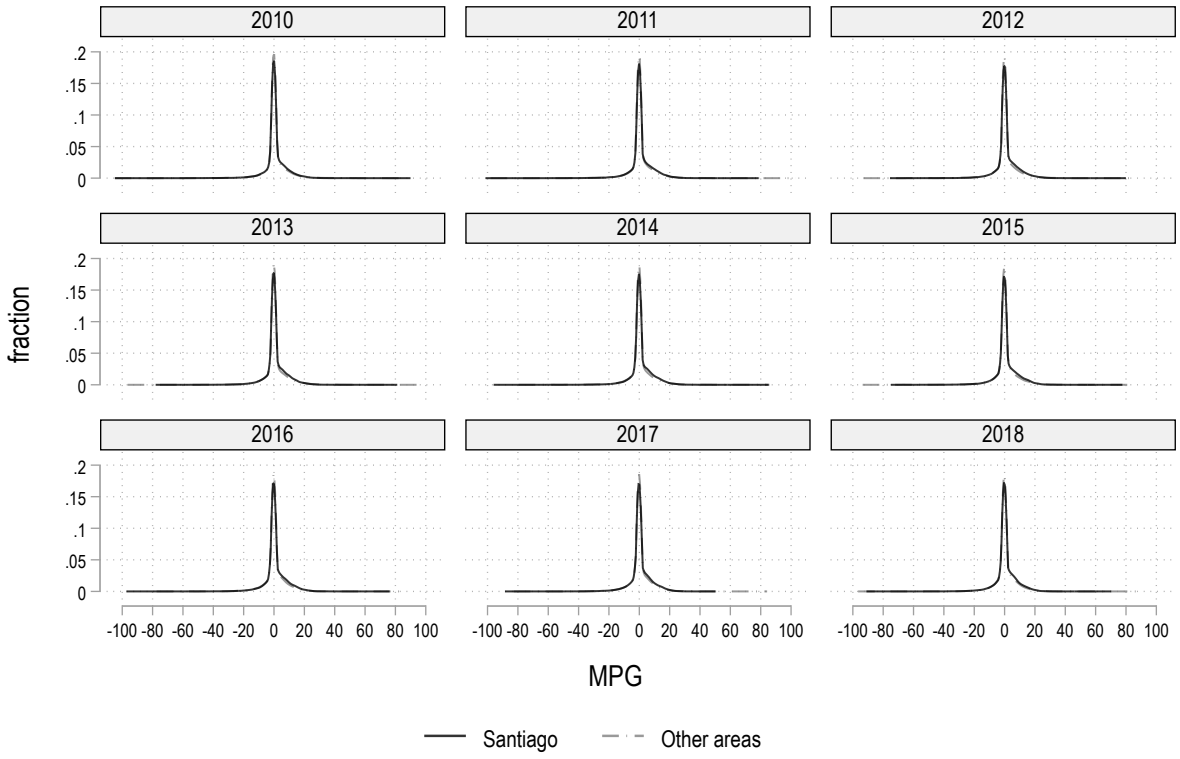
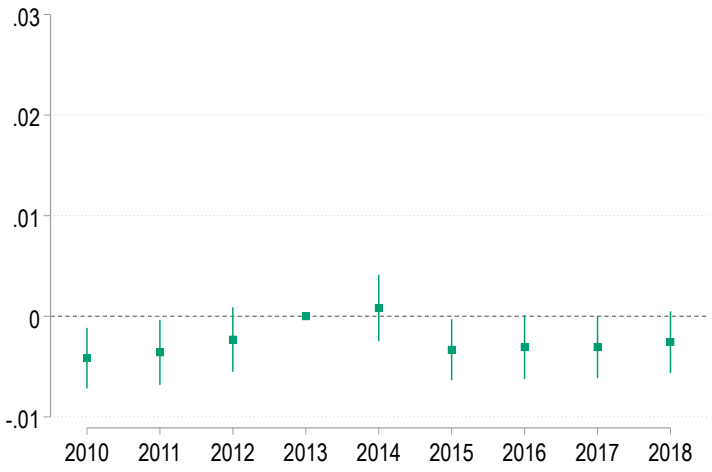
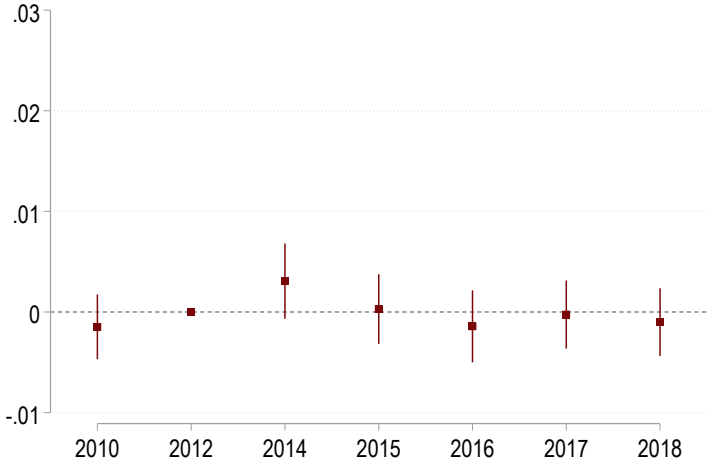


FIGURE A6. Median Potential Gain's Distribution by Year and Area.

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 A7. 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 2014. 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.

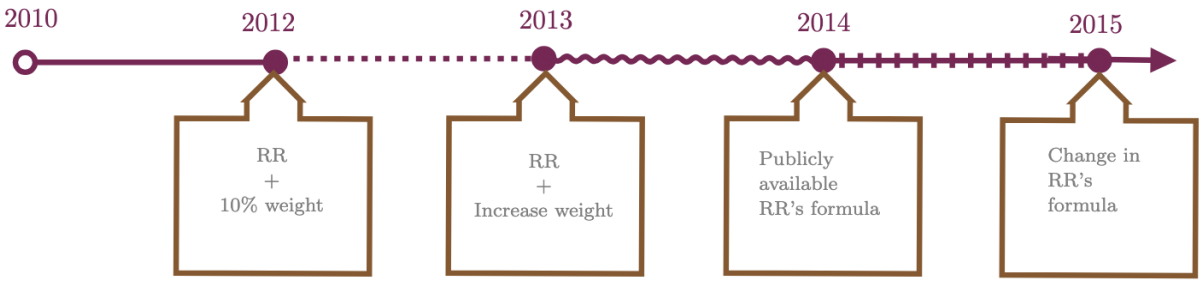


FIGURE A8. Relative Ranking Policy's Timeline

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.

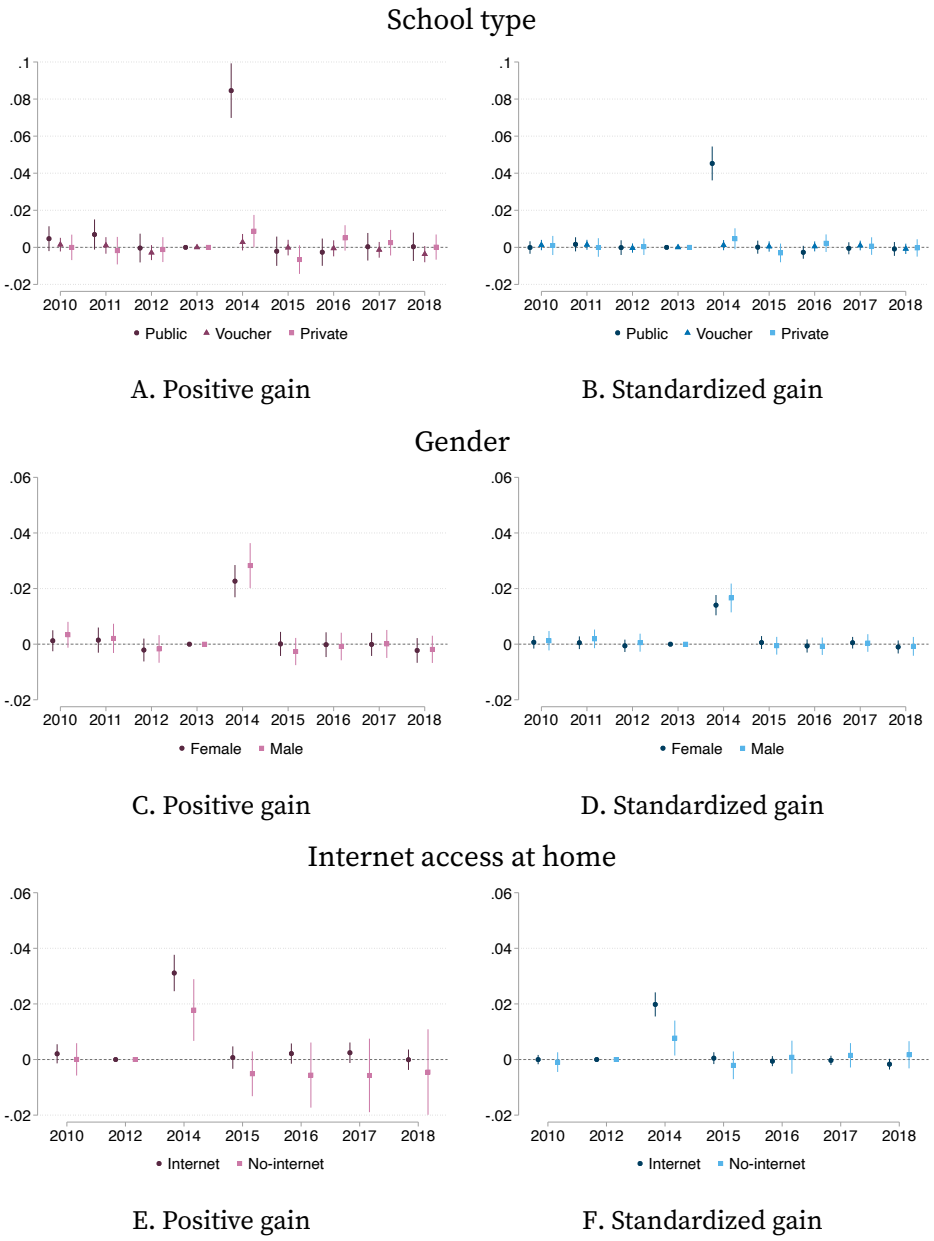
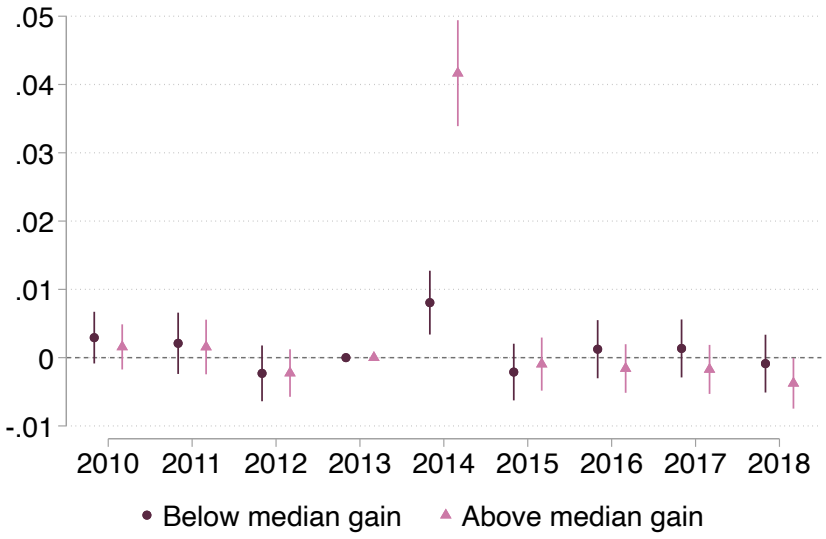
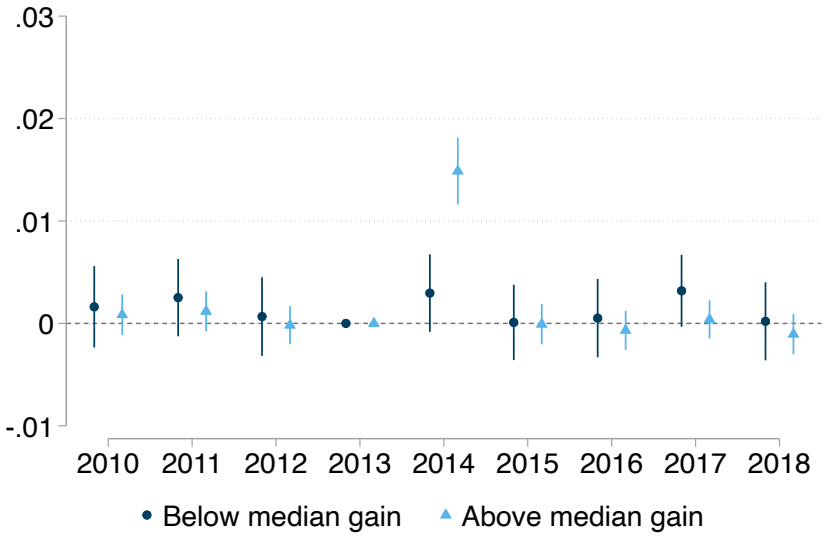


FIGURE A9. Heterogeneous Impact of the RR Policy Disclosure on School Switching, Additional Splits

Note: This figure plots the coefficients from estimating Equation (4) separately by group, where the outcome is an indicator for switching schools in twelfth grade. In the left figures the key regressors are the interactions between an indicator for having a positive median potential gain and event year dummies; in the right figures, the interactions between the median potential gain, standardized within the graduating cohort, and event year dummies. The first two figures present the results by school type (public, voucher, or private), the next two by gender, and the last two by whether the student has internet access at home. Gender and internet access come from the parent questionnaire of the tenth-grade SIMCE test, which was not administered to the cohorts finishing twelfth grade in 2011 and 2013, so in those four figures the two cohorts are excluded and 2012 is the omitted year; the school-type figures use all cohorts entering twelfth grade between 2010 and 2018, with 2013 as the omitted year. The event of interest is the release of the RR policy formula in 2014. The sample is students living in Gran Santiago during primary and secondary school and attending a secondary school in the area. All regressions include fixed effects for within-school GPA deciles and for the school where the student starts twelfth grade. The y-axis reports the change in the probability of switching relative to the omitted year; in the right figures this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the school-market level, and 99% confidence intervals are shown.



A. Positive gain



B. Standardized gain

FIGURE A10. Impact of the RR Policy Disclosure on Students' School Switching by the Size of the Potential Gain

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. Among students with a positive median potential gain, those above and below the median gain are estimated separately, each against the same untreated comparison group. Both panels include fixed effects for the school the student attends at the start of twelfth grade and for within-school GPA deciles. Panel A uses the discrete treatment, an indicator for a positive median potential gain, and Panel B the continuous treatment, the median potential gain standardized within cohort. The event of interest is the release of the RR policy formula in 2014. The sample is restricted to students living in Gran Santiago during primary and secondary school. 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.

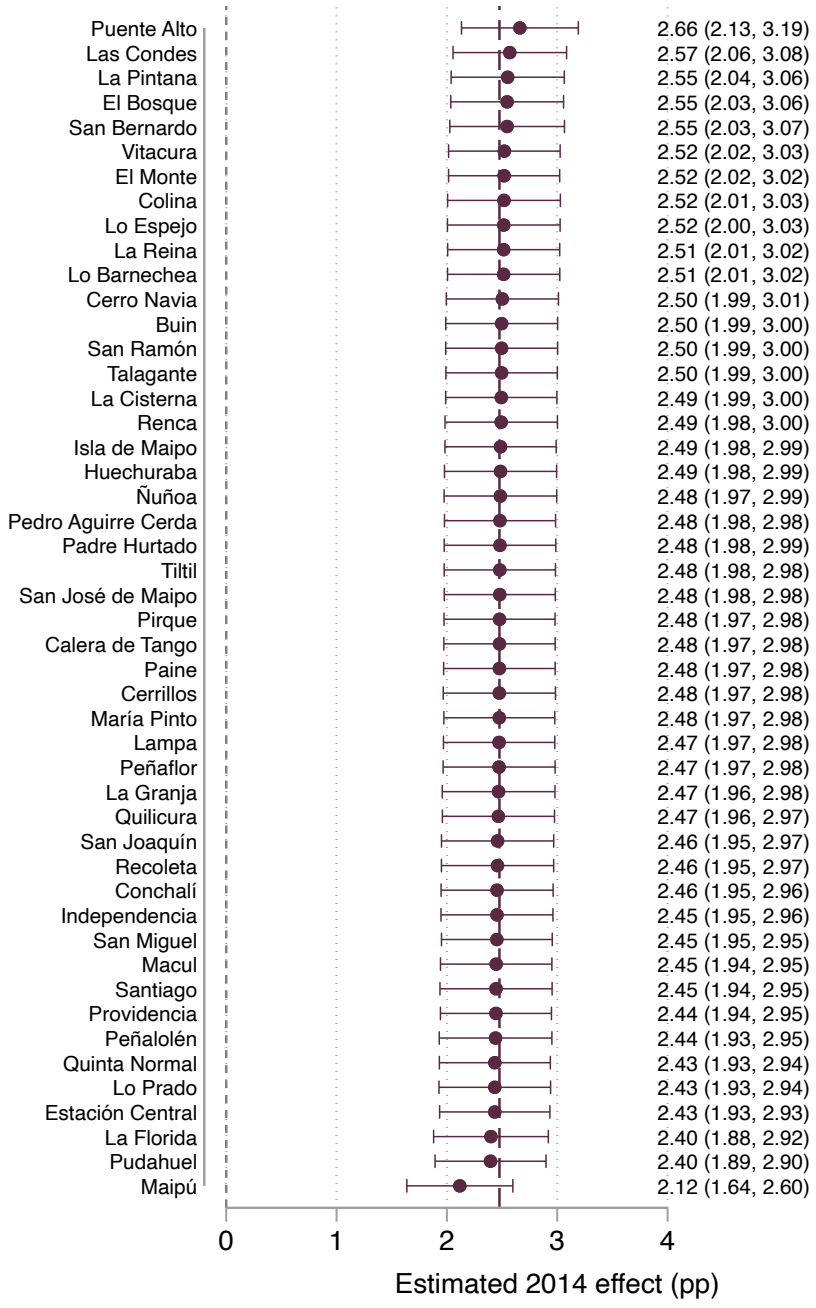


FIGURE A11. Leave-One-County-Out Estimates: Positive Gain

Note: Each row reports the 2014 coefficient from the regression of students' switching schools in twelfth grade on the interaction between the discrete treatment, an indicator for a positive median potential gain, and event-year dummies, following equation (4), after excluding the students who lived in that county (comuna) during primary school. The specification is re-estimated once for each of the 48 counties of Gran Santiago. Dots are point estimates, horizontal lines are 99% confidence intervals, and the estimate and interval are printed to the right of each row. The dashed vertical line marks the estimate on the full sample and the grey line marks zero. The specification includes fixed effects for the school the student attends at the start of twelfth grade and for within-school GPA deciles, and restricts the sample to students living in Gran Santiago during primary and secondary school. Standard errors are clustered at the school-market level.

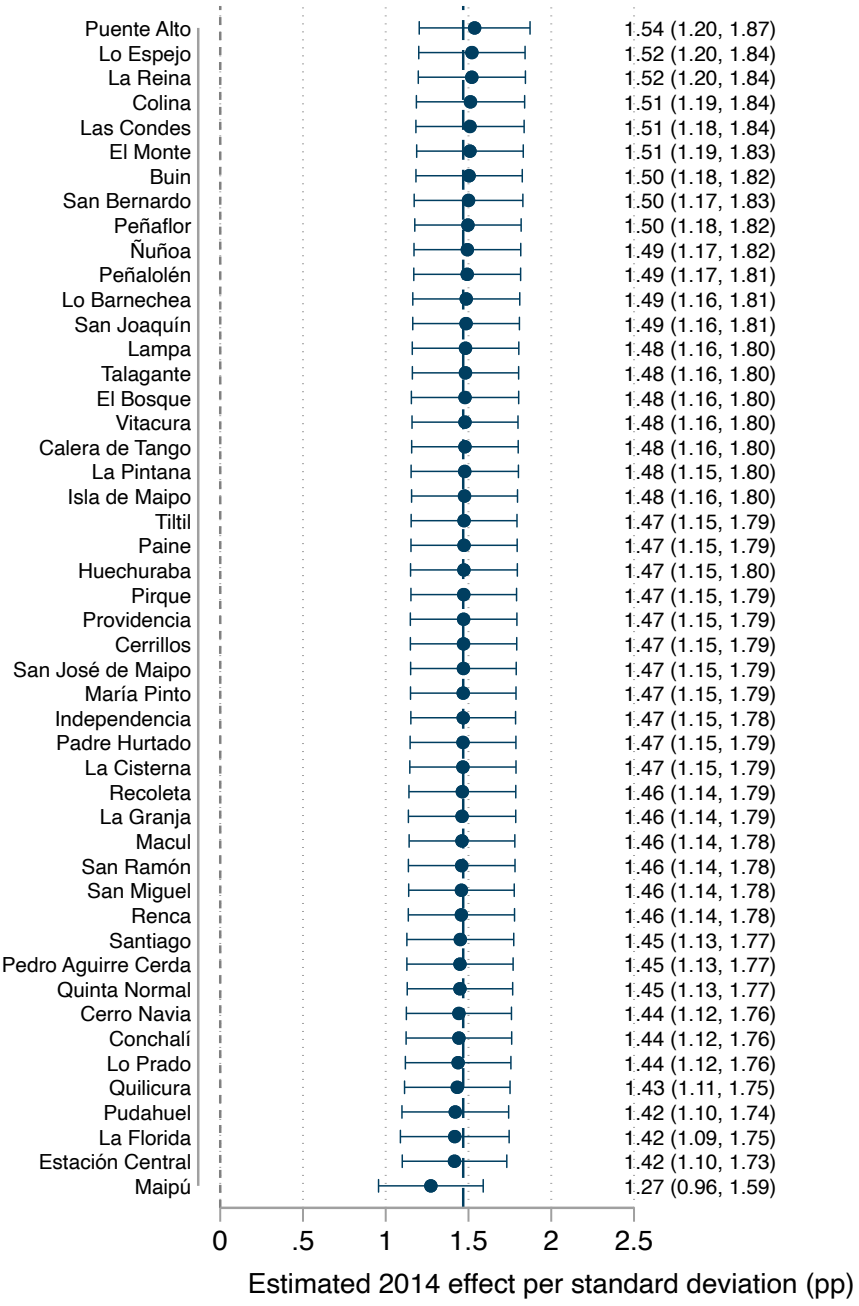


FIGURE A12. Leave-One-County-Out Estimates: Standardized Gain

Note: Each row reports the 2014 coefficient from the regression of students' switching schools in twelfth grade on the interaction between the continuous treatment, the median potential gain standardized within cohort, and event-year dummies, following equation (4), after excluding the students who lived in that county during primary school. The specification is re-estimated once for each of the 48 counties of Gran Santiago. Dots are point estimates, horizontal lines are 99% confidence intervals, and the estimate and interval are printed to the right of each row. The dashed vertical line marks the estimate on the full sample and the grey line marks zero. The specification includes fixed effects for the school the student attends at the start of twelfth grade and for within-school GPA deciles, and restricts the sample to students living in Gran Santiago during primary and secondary school. Standard errors are clustered at the school-market level.

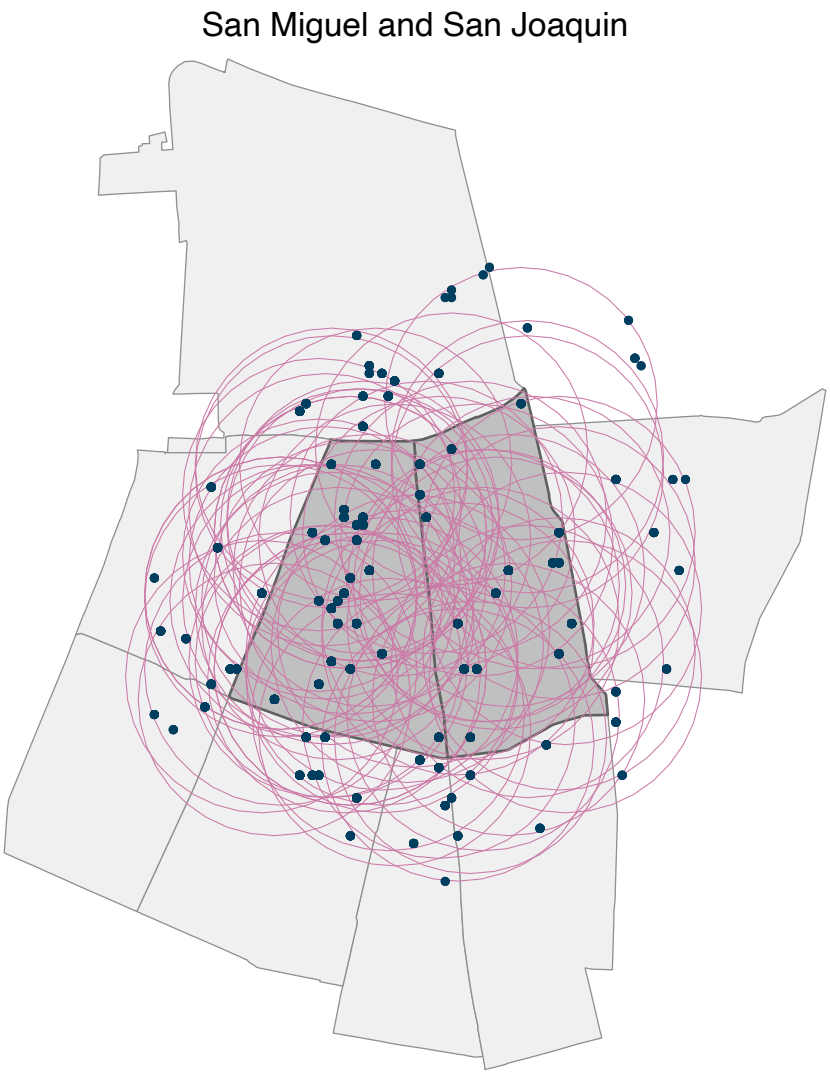
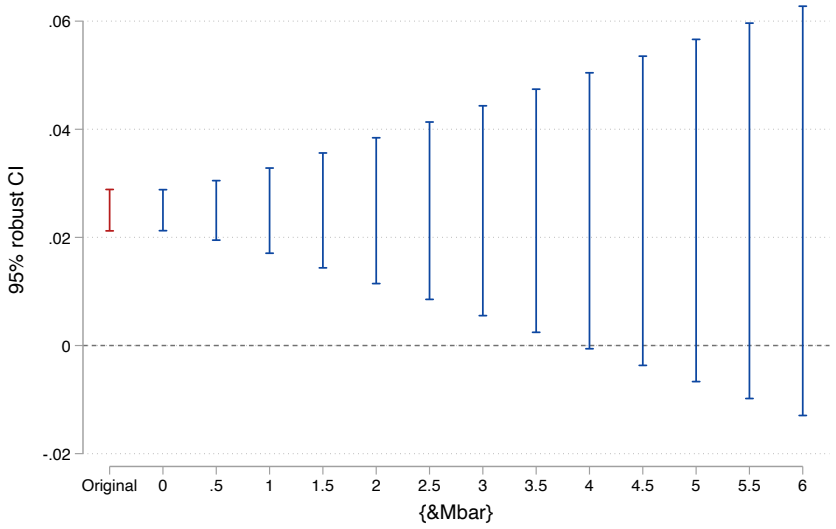
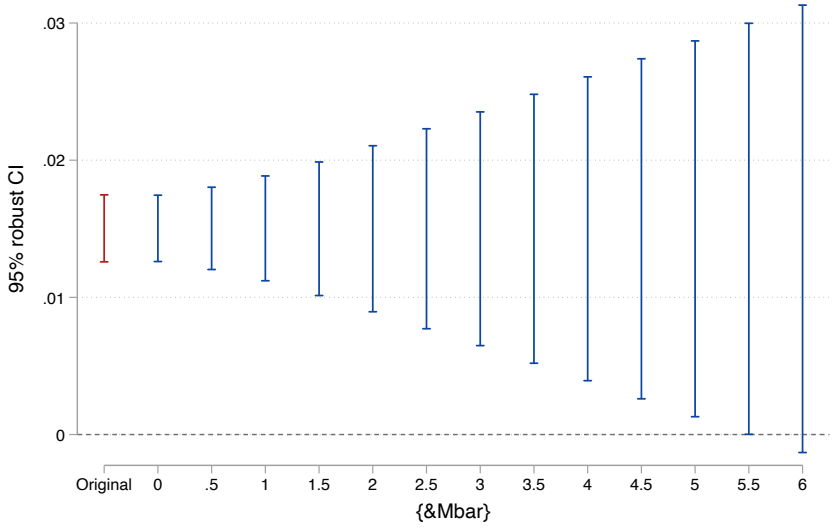


FIGURE A13. School Markets for Two Adjacent Counties

Note: This figure shows the 2 km school markets of students living in San Miguel and San Joaquín counties during primary school. Each circle is one student's market, centered on the primary school they attended, and dots mark the location of every secondary school. The dark gray area, divided by the shared boundary, marks San Miguel (left) and San Joaquín (right), light gray marks the surrounding counties.



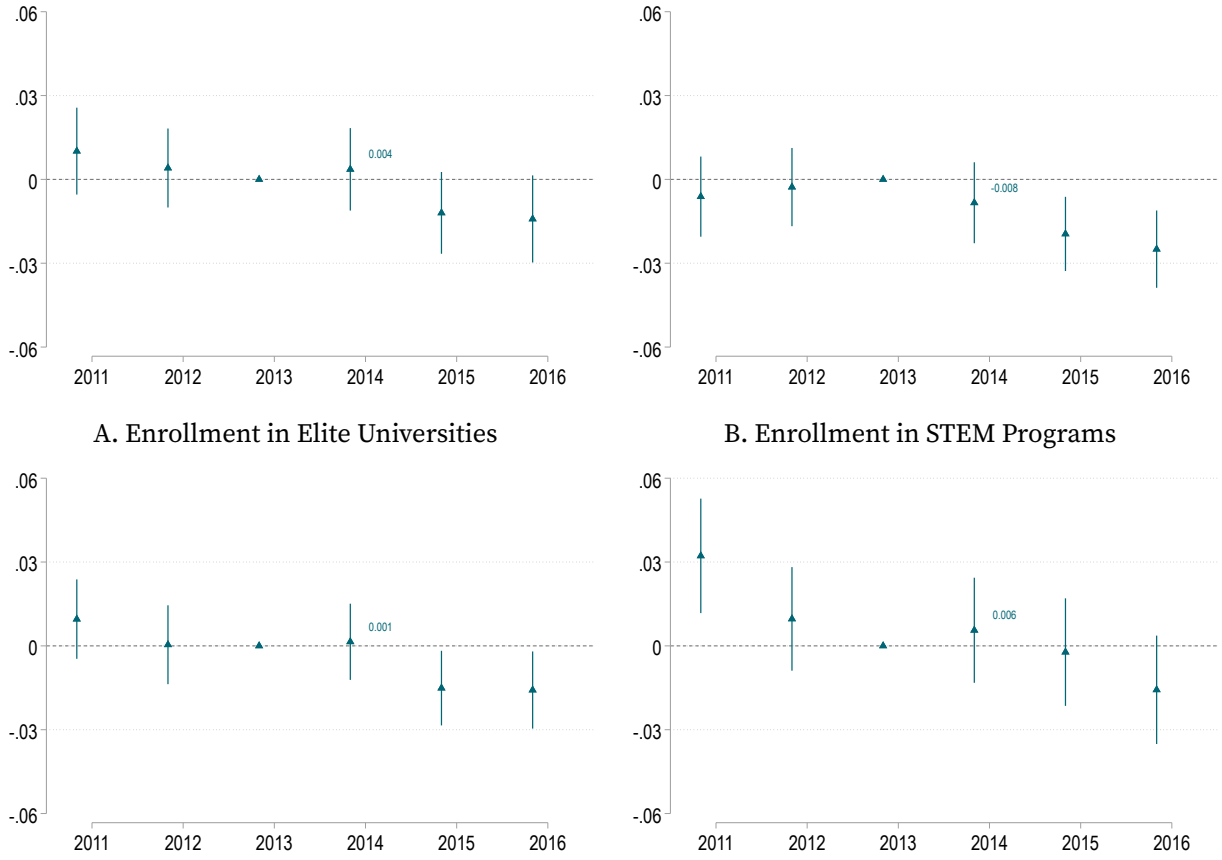
A. Positive gain



B. Standardized gain

FIGURE A14. Sensitivity of the 2014 Estimate to Differential Trends

Note: This figure reports how sensitive the 2014 estimate is to violations of parallel trends, following Rambachan and Roth (2023). The object of interest is the 2014 coefficient from equation (4), estimated on its own rather than averaged with later years. Each interval is the 95% robust confidence interval for that coefficient when the difference in trends between the two groups after the disclosure is allowed to be up to $\bar{M}$ times the largest year-on-year difference observed before it; the leftmost interval is the one from the original specification. Panel A uses the discrete treatment, an indicator for a positive median potential gain, and Panel B the continuous treatment, the median potential gain standardized within cohort. Both include fixed effects for the school the student attends at the start of twelfth grade and for within-school GPA deciles. The sample is restricted to students living in Gran Santiago during primary and secondary school who attend a school located in Gran Santiago. Standard errors are clustered at the school-market level. The 2014 estimate stays distinguishable from zero as long as the difference in trends after the disclosure is no more than 3.9 times the largest one observed before it for the discrete measure (Panel A), and 5.5 times for the continuous measure (Panel B).



A. Enrollment in Elite Universities

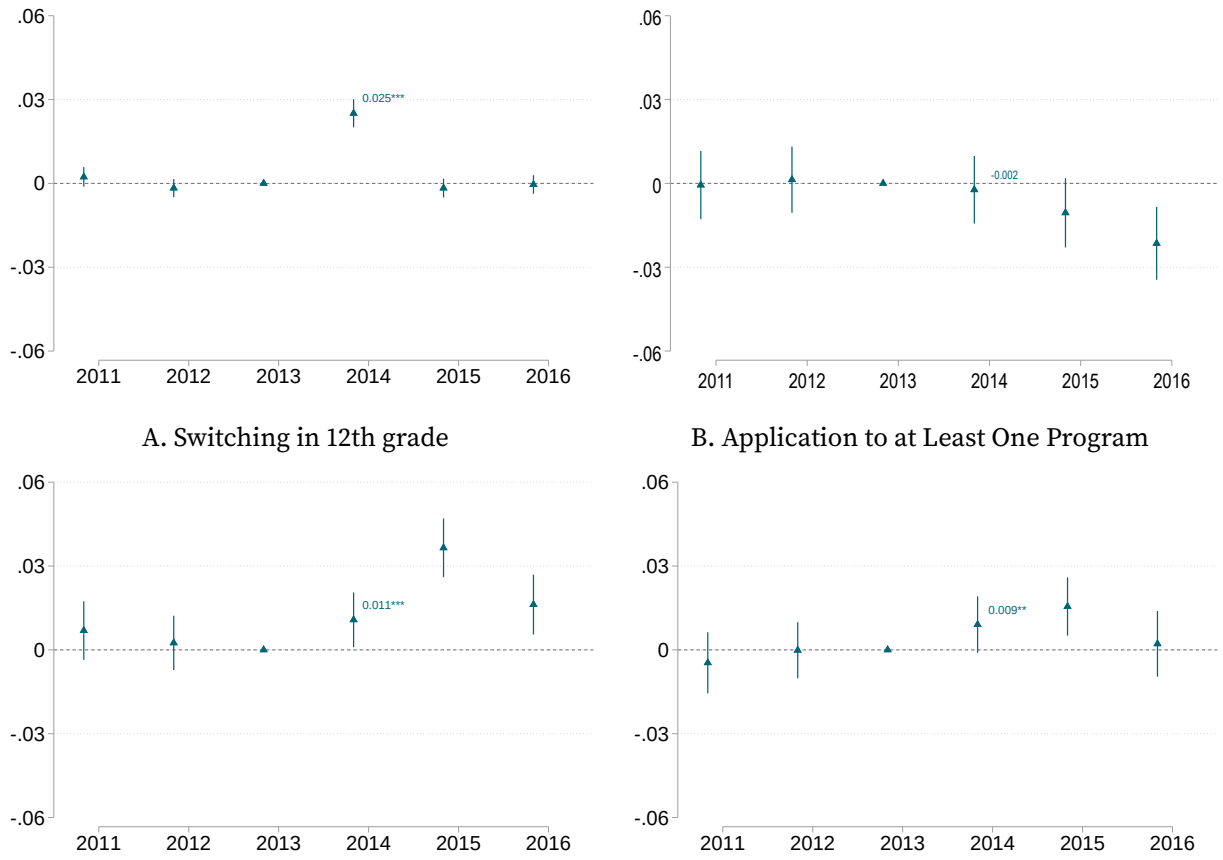
B. Enrollment in STEM Programs

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 2014. 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

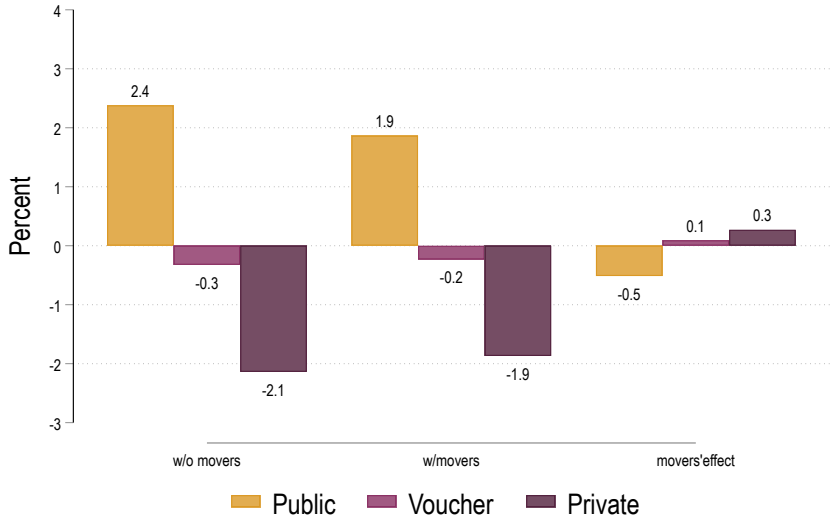
B. Application to at Least One Program

C. Application: Elite University

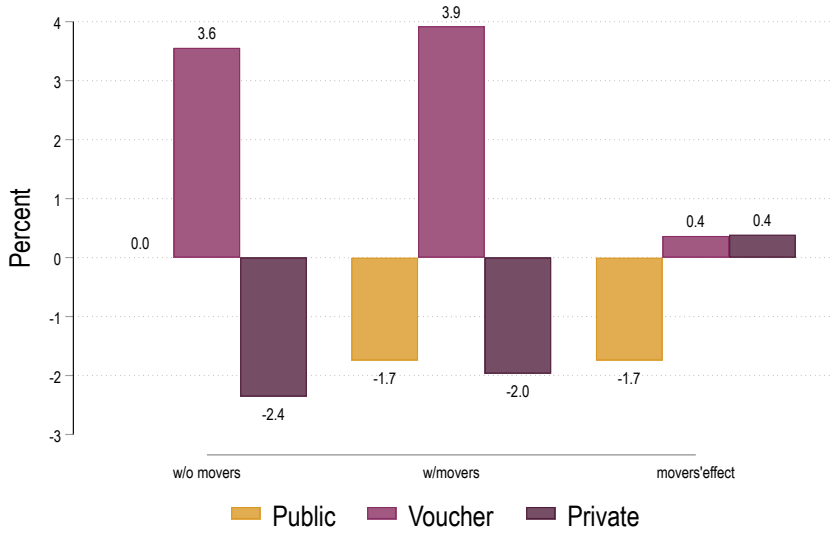
D. Application: Highly Selective Program

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 2014. 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% (*).



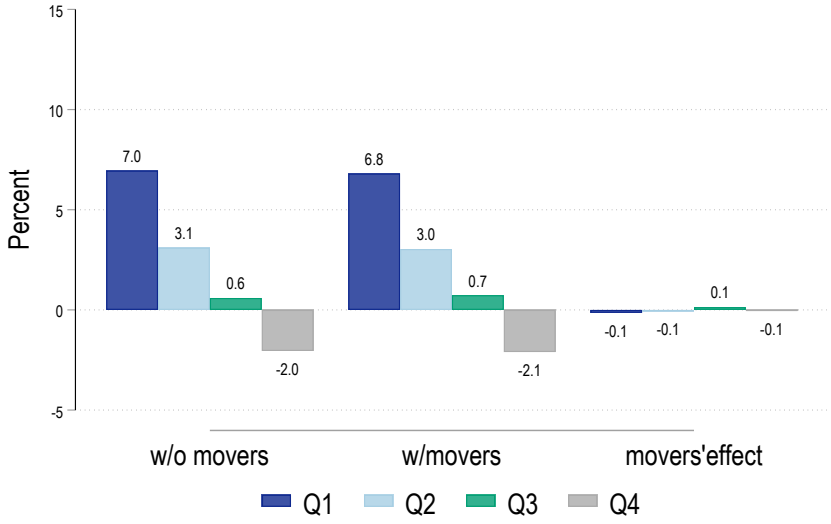
A. Overall System



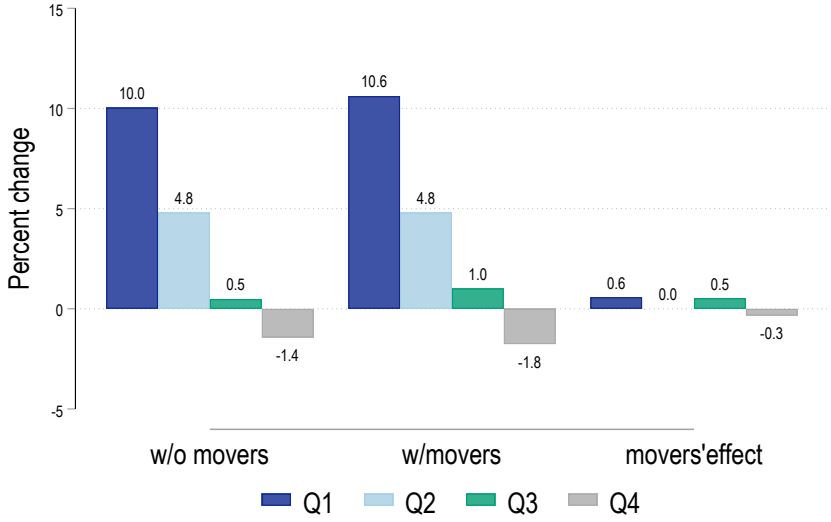
B. Tier 1 Universites

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.



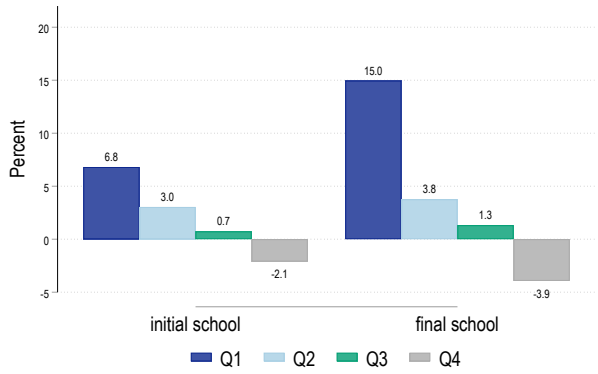
A. Overall System



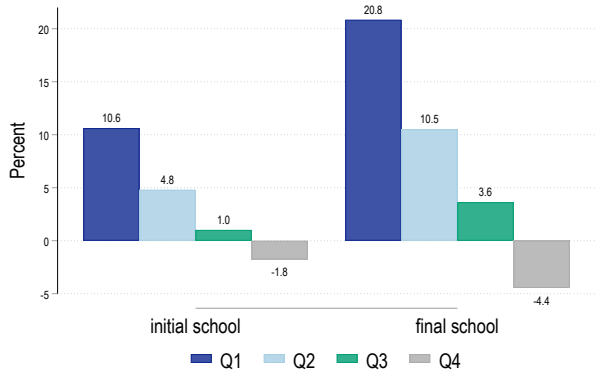
B. Tier 1 Universites

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.[44] 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).[45]

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,[46] 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.

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

[IT NEED REWRITING FOR NEW GRAPHS AND NEW MEASURES AND DIFFERENT BUFFERS OF RADIUS]

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.

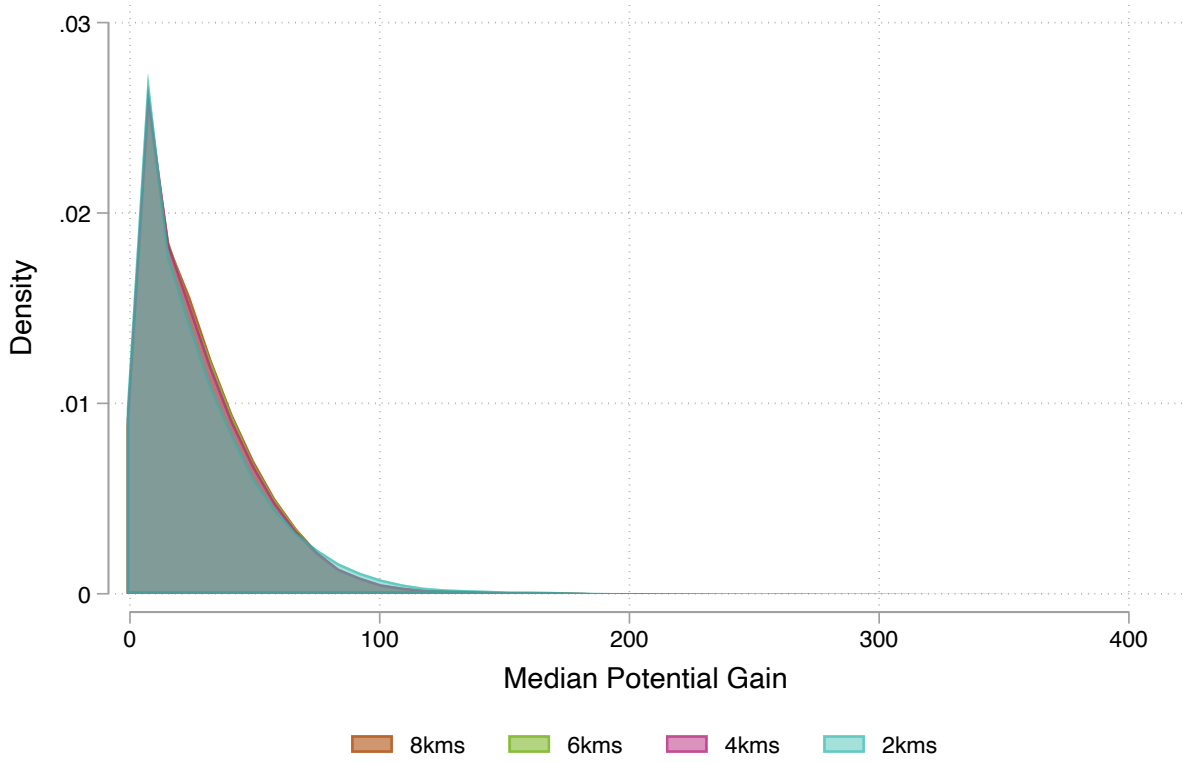


FIGURE A20. Positive Median Potential Gain Distribution.

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 Measures and School Market Characteristics

[MODIFY ENTIRELY]

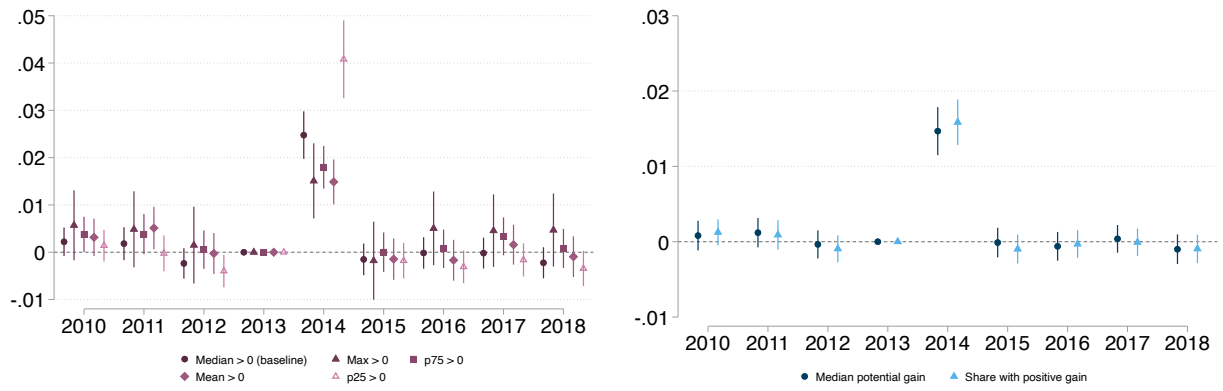
This appendix examines whether the results depend on two choices: how the incentive a student faces is measured, and the market over which that incentive is computed. The first part reports the event study under alternative definitions of the potential gain, binary and continuous. The second describes how many schools students have within reach and estimates the response separately for students with few and many alternatives.

E.1. Alternative Definitions of the Potential Gain

Figure A21 presents the main event-study estimates for the probability of switching schools during twelfth grade, from equation (4), under alternative definitions of the treatment variable. The baseline specification (used throughout the paper) uses the median potential gain across schools in the student's local market.

As described in Section 4, the baseline discrete treatment variable is a binary indicator equal to one if student i has a positive median potential gain across schools in their local market. Each of the binary alternatives is a threshold on the fraction of the schools in the student's market that would raise their ranking, and they differ only in how large that fraction must be. The baseline median potential gain requires at least half. I consider four binary alternatives: (i) *maximum potential gain*, $Max > 0$, equal to one if the highest potential gain in the student's market is positive, which requires at least one school; (ii) *75th percentile*, $p75 > 0$, equal to one if the 75th percentile of the potential gains in their market is positive, which requires at least a quarter of the schools; (iii) *mean potential gain*, $Mean > 0$, equal to one if the average potential gain is positive; and (iv) *25th percentile*, $p25 > 0$, equal to one if the 25th percentile of the potential gains is positive, which requires at least three quarters of the schools in the market. Figure A21, Panel A, presents the event study for the discrete measures.

The results under any of the measures follow a similar shape: flat before 2014, a sharp increase in switching in 2014, when the policy's formula was disclosed in the guidelines, and a return to zero thereafter. What changes is the magnitude, which rises as the definition requires more of the market to be worth moving to, while the treated group shrinks. The 2014 estimate is 1.5 pp under the maximum, which treats 89.7% of students; 1.8 pp under the 75th percentile, with 65.5% of students treated; 1.5 pp under the mean (70.3%), 2.5 pp under the baseline median (38.4%); and 4.1 pp under the 25th percentile (17.7%). Joint tests of each measure against the baseline reports differences of −0.96 pp for the maximum, −0.67 pp for the 75th percentile, −0.98 pp for the mean, and +1.59 pp for the 25th percentile, all significant at a 1% level. Since the definitions are nested, a looser one moves students from the comparison group into the treated group, so the estimate falling as the definition loosen means those students respond less than the ones already included. The response is nonetheless positive and statistically significant under every definition, including



A. Positive gain

B. Standardized gain

FIGURE A21. Impact of the RR Policy Disclosure on Students' Switching Schools during Twelfth Grade under Alternative Treatment Definitions

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, following equation (4). All specifications include fixed effects for the school the student attends at the start of twelfth grade and for within-school GPA deciles. The event of interest is the release of the RR policy's formula in 2014. Both panels restrict the sample to students living in Gran Santiago during primary and secondary school. Panel A reports the discrete baseline definition and four binary alternatives; Panel B reports the baseline measures entering continuously and one alternative, each standardized within cohort. The y-axis shows 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.

the one that asks only for a single school in the market to raise the student's ranking.

Panel B of Figure A21 presents the event study estimates under two continuous measures. The baseline measure also enters continuously, as the median potential gain in the student's market, and I report one alternative to it: the share of schools in the market that give the student a positive gain. The two summarize different features of the same distribution of gains: the median measures how much the typical school in the market would raise the student's ranking, while the share of schools with a positive gain measures how much of the market would raise it at all. They nonetheless deliver very similar point estimates: a one standard deviation increase in the median gain raises the probability of switching in 2014 by 1.47 pp, and a one standard deviation increase in the share of schools with a positive gain by 1.59 pp; the difference of 0.12 pp is not statistically different from zero ($p = 0.134$).

E.2. Responses under Different Sizes of School Markets

The measures above describe the gains a market offers. The number of schools a student has within reach and the number worth moving to are different objects, and only the latter should affect student's responses. In Gran Santiago the number of schools in the market and the potential gain are in fact essentially uncorrelated (correlation of −0.07). Whether a nearby school raises a student's ranking depends on their own GPA, on that school's threshold and on the threshold of the school they attend, so a market can be large without offering much.

Figure A22 reports the distribution of market size, including lines for the 25th, 50th and 75th percentile. The dashed line shows the mean of the distribution, that is 18.1 schools, slightly higher than the median of 16 schools. Figure A23 tests the importance of the number of alternatives by estimating the event study separately above and below the median, dividing students into groups facing 9.3 and 26.2 schools on average. Having a positive median gain raises the probability of switching in 2014 by 2.2 pp in the smaller-market group and 2.8 pp in the larger-market group, and equality is not rejected at any significance level lower than 9.1%; under the continuous measure the estimates are 1.3 pp and 1.6 pp per standard deviation, and equality is again not rejected at any standard significance level. The size of a market does not predict the response because it does not predict how much of that market is worth moving to.

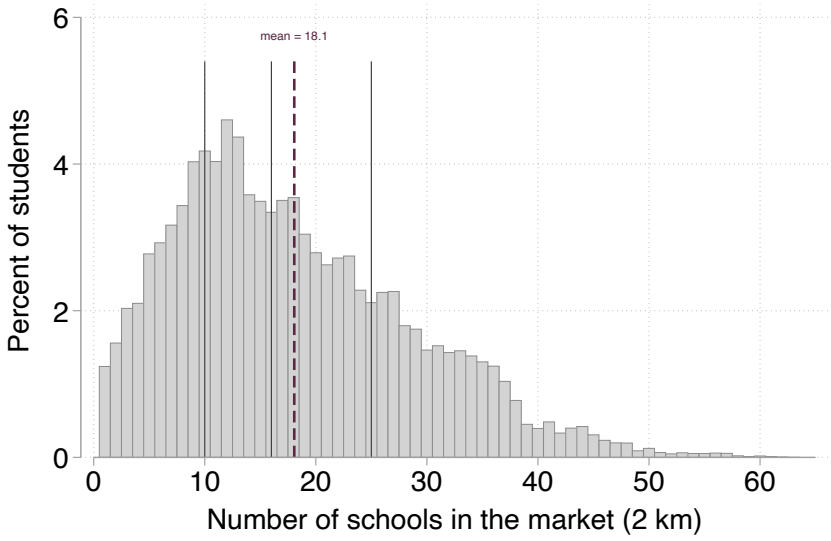
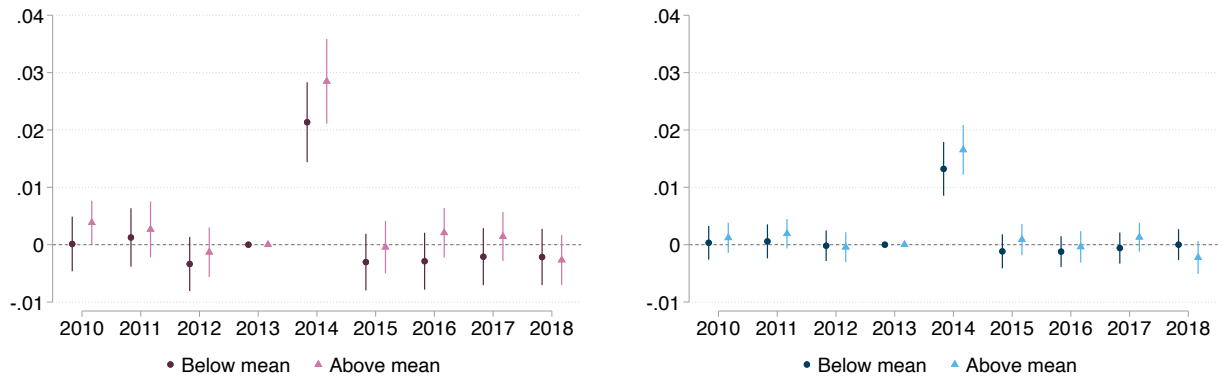


FIGURE A22. Distribution of the Number of Alternative Schools in Students' Local Markets

Note: This figure presents the distribution of the number of schools available to a student within 2 km of the school attended during primary school, pooling the cohorts graduating between 2010 and 2018 and restricting the sample to students living in Gran Santiago during primary and secondary school. Each bar reports the percentage of students facing that number of alternatives. The solid vertical lines mark the 25th, 50th, and 75th percentiles of the distribution and the dashed line marks the mean.



A. Positive gain

B. Standardized gain

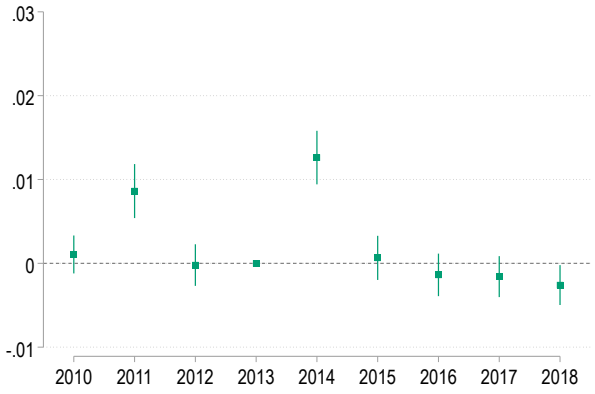
FIGURE A23. Impact of the RR Policy Disclosure on Students' School Switching by the Number of Alternative High Schools in the Local Market

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. Students are divided at the median number of schools located within 2 km of the school they attended in primary, computed within cohort. Both panels include fixed effects for the school the student attends at the start of twelfth grade and for within-school GPA deciles. Panel A uses the discrete treatment, an indicator for a positive median potential gain, and Panel B the continuous treatment, the median potential gain standardized within cohort. The event of interest is the release of the RR policy formula in 2014. The sample is restricted to students living in Gran Santiago during primary and secondary school. 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.

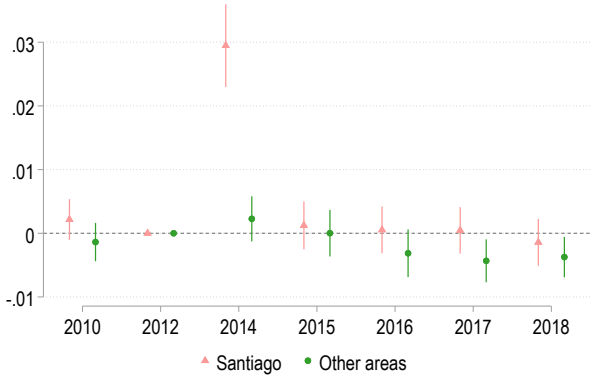
Appendix F. Analysis using sample of students living in the same county than in primary school

[THIS MIGHT NOT NEED TO BE A FULL APPENDIX AND ONLY TWO FIGURES (FOR HIGH SCHOOL AND HIGHER EDUCATION OUTCOMES IN THE APPENDIX 1]

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 A24 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 (Panel B) using the main treatment specification.



A. Chile



B. Santiago

FIGURE A24. 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 2014. 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 G. Policy Intensity and the Timing of the Response

[NEW APPENDIX]

The spike observed in the 2014 in the likelihood that students switch schools during twelfth grade admits at least two competing interpretations, policy salience and policy bite. Figure A25 and Table A10 present evidence in favor of the salience interpretation.

Through the paper, I interpret *policy salience* as a shock that makes students more aware of how the RR is constructed. The RR had been publicly discussed since 2012, the year when was first implemented, and appeared in the official guidelines students consult since 2013, but its construction was poorly explained. I argue that the relevant shock is the change in how it was presented in the guidelines. Figure A26 reproduces the corresponding sections of the guidelines for the 2014 and 2015 admission process, which correspond to the years where students would start tertiary education. In 2014 it has its own section, which states separately what happens to students below their school's historic average, and includes a figure plotting the ranking score against a student's grade average. *Policy bite*it was , by contrast, refers to an increase in the weights the RR carries in the college admission score.

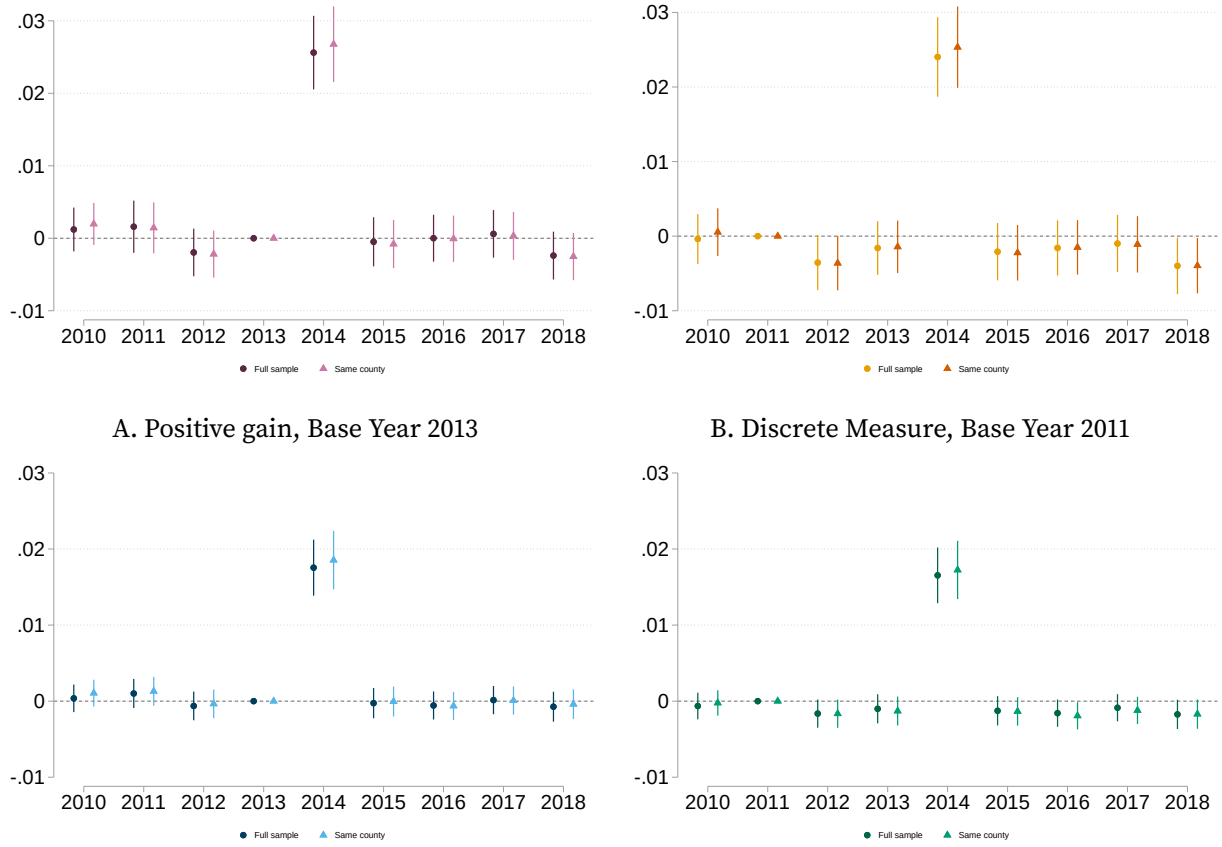
To try to separate the two, I compute the average weight assigned to the RR and to the GPA in the centralized admission system. Table A10 shows the averages for all participating universities and separately by selectivity tier. The RR weight rises twice: for the 2012 cohort, when the component is introduced at 10 percent, and for the 2013 cohort, when it reaches 22.2 percent on average. In both cases the increase comes mostly from a reduction in the weight on GPA. Between the 2013 cohort, which is the base year in the main analysis, and the 2014 cohort, the weight changes by 0.76 percentage points (p.p.) across all programs, by 0.10 p.p. in tier 1 and by -0.27 p.p. in tier 2. The change is statistically indistinguishable from zero in the two selective tiers, and while the overall difference is marginally significan ($p = 0.052$), it is less than a percentage point in a base of 22 percent. The incentive facing 2014 cohort was therefore essentially the one facing the cohort before it.

Because the policy was introduced for the 2012 cohort (admission process 2013), and the weights rose for the 2013 cohort, I also re-estimate the main specification using 2011 as the base year. Figure A25 shows no increase in switching in either 2012 or 2013. If anything, the coefficients for those years are negative and an order of magnitude smaller than the 2014 estimate. I report results for the preferred measure, an indicator equal to one when a student has a positive potential gain (Panels A and B), and for the standardized continuous potential gain (Panels C and D).

TABLE A10. RR and GPA Weights in the Centralized Admission System for Academic Years 2010 - 2018

	All programs		Tier 1		Tier 2		Tier 3	
Year	RR	GPA	RR	GPA	RR	GPA	RR	GPA
2010	0.00	30.20	0.00	24.42	0.00	29.53	0.00	28.90
2011	0.00	29.33	0.00	24.56	0.00	27.30	0.00	27.66
2012	10.00	23.33	10.00	19.29	10.00	26.63	10.00	20.52
2013	22.21	16.05	19.90	17.65	29.52	11.15	18.43	17.02
2014	22.98	15.78	20.00	17.62	29.25	11.27	19.89	16.55
2015	23.87	15.73	20.00	17.62	29.17	11.42	20.83	16.70
2016	24.70	15.26	21.24	16.49	29.02	11.56	21.70	16.14
2017	24.05	14.32	21.13	16.60	28.41	11.42	22.29	15.79
2018	24.35	14.07	20.56	16.48	28.82	11.32	22.24	15.87
Difference 2014 – 2013	0.763		0.102		-0.274		1.460	
	(0.393)		(0.753)		(1.931)		(0.354)	
p-value	0.052		0.892		0.887		0.000	

Note: This table reports the mean weight assigned to the relative ranking (RR) and to the GPA component of the admission score across all programs participating in the centralized admission system, overall and separately by university selectivity tier. Tiers follow Kapor, Karnani, and Neilson (2024). The year column is the graduating cohort: a student graduating in year t applies in December of that year for the admission process of $t + 1$, so the weights reported for the 2014 cohort are those of the 2015 admission process. The RR component did not exist before the 2013 process and is therefore set to zero for the 2010 and 2011 cohorts. The final rows report the difference in the mean ranking weight between the 2014 and 2013 cohorts, its standard error, and the p-value from a two-sample test allowing for unequal variances. The number of programs ranges from 980 to 1,806 overall, from 86 to 108 in Tier 1, from 64 to 116 in Tier 2, and from 445 to 630 in Tier 3.



A. Positive gain, Base Year 2013

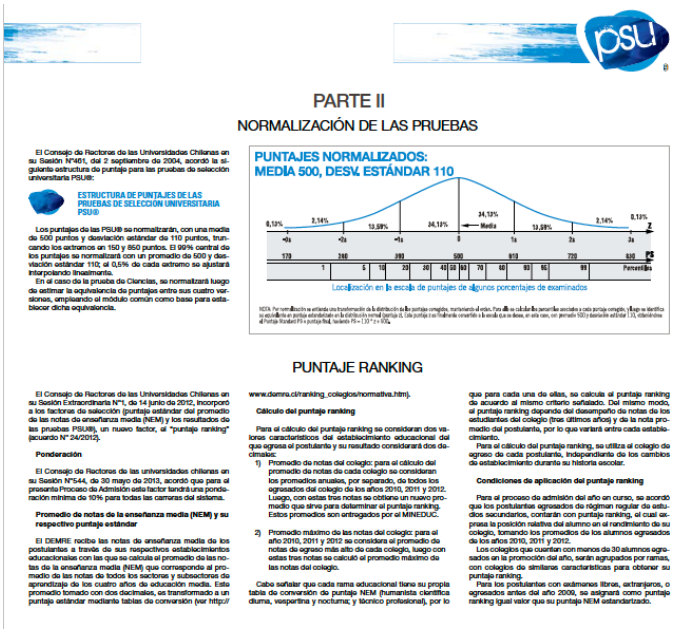
B. Discrete Measure, Base Year 2011

C. Standardized gain, Base Year 2013

D. Continuous Measure, Base Year 2011

FIGURE A25. Switching Schools During 12th Grade, Alternative Base Years and Measures of Potential Gain

Note: This figure plots the interaction coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade. In Panels A and B the key regressors are the interactions between having a positive potential gain and event-year dummies; in Panels C and D they are the interactions between the student's median potential gain, standardized within their graduating cohort, and event-year dummies. All panels include fixed effects for the school the student attends at the start of grade 12 and for within-school GPA deciles, and are estimated on students living in Gran Santiago. Circles report estimates for the full sample and triangles restrict it to students who live in the same county in primary and secondary school. Panels A and C report estimates relative to 2013, the preferred specification, and Panels B and D relative to 2011, so the coefficient for the 2013 cohort, the first under the RR policy to face the higher ranking weight, is observable. The y-axis shows the change in the probability of switching relative to the omitted year; in Panels C and D this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the students' market level, and 95% confidence intervals are displayed.



PARTE II

NORMALIZACIÓN DE LAS PRUEBAS

El Consejo de Rectores de las Universidades Chilenas en su Sesión N°401, del 2 septiembre de 2004, acordó la siguiente estructura de puntaje para las pruebas de selección universitaria PSU®:

ESTRUCTURA DE PUNTAJES DE LAS PRUEBAS DE SELECCIÓN UNIVERSITARIA PSU®

Los puntajes de las PSU® se normalizarán, con una media de 500 puntos y desviación estándar de 110 puntos, truncando los extremos en 150 y 850 puntos. El 99% central de los puntajes se normalizará con un promedio de 500 y desviación estándar 110; el 0,5% de cada extremo se ajustará interpolando linealmente.

En el caso de la prueba de Ciencias, se normalizará luego de estimar la equivalencia de puntajes entre sus cuatro versiones, ampliando el módulo común como base para establecer dicha equivalencia.

PUNTAJES NORMALIZADOS: MEDIA 500, DESV. ESTÁNDAR 110

0,13% 2,14% 13,59% 34,13% 34,13% Media 13,59% 2,14% 0,13%

-3s -2s -1s 0 1s 2s 3s

170 280 390 500 610 720 830 PS

1 5 10 20 40 60 80 90 95 99 Percentiles

Localización en la escala de puntajes de algunos porcentajes de examinados

PUNTAJE RANKING

El Consejo de Rectores de las Universidades Chilenas en su Sesión Extraordinaria N°1, de 14 junio de 2012, incorporó a los factores de selección (puntaje estándar del promedio de las notas de enseñanza media (NEM) y los resultados de las pruebas PSU®), un nuevo factor, el "puntaje ranking" (acuerdo N° 24/2012).

Ponderación

El Consejo de Rectores de las universidades chilenas en su Sesión N°544, de 30 mayo de 2013, acordó que para el presente Proceso de Admisión este factor tendrá una ponderación mínima de 10% para todas las carreras del sistema.

Promedio de notas de la enseñanza media (NEM) y su respectivo puntaje estándar

El DEMRE recibe las notas de enseñanza media de los postulantes a través de sus respectivos establecimientos educacionales con las que se calcula el promedio de las notas de la enseñanza media (NEM) que corresponde al promedio de las notas de todos los sectores y subsectores de aprendizaje de los cuatro años de educación media. Este promedio tomado con dos decimales, es transformado a un puntaje estándar mediante tablas de conversión (ver http://www.demre.cl/ranking_coleglos/normativa.htm).

Cálculo del puntaje ranking

Para el cálculo del puntaje ranking se consideran dos valores característicos del establecimiento educacional del que egresa el postulante y su resultado considerará dos decimales:

1) Promedio de notas del colegio: para el cálculo del promedio de notas de cada colegio se consideran los promedios anuales, por separado, de todos los egresados del colegio de los años 2010, 2011 y 2012. Luego, con estas tres notas se obtiene un nuevo promedio que sirve para determinar el puntaje ranking. Estos promedios son entregados por el MINEDUC.

2) Promedio máximo de las notas del colegio: para el año 2010, 2011 y 2012 se considera el promedio de notas de egreso más alto de cada colegio, luego con estas tres notas se calculó el promedio máximo de las notas del colegio.

Cabe señalar que cada rama educacional tiene su propia tabla de conversión de puntaje NEM (humanista científica diurna, vespertina y nocturna; y técnico profesional), por lo que para cada una de ellas, se calcula el puntaje ranking de acuerdo al mismo criterio señalado. Del mismo modo, el puntaje ranking dependa del desempeño de notas de los estudiantes del colegio (tres últimos años) y de la nota promedio del postulante, por lo que variará entre cada establecimiento.

Para el cálculo del puntaje ranking, se utiliza el colegio de egreso de cada postulante, independiente de los cambios de establecimiento durante su historia escolar.

Condiciones de aplicación del puntaje ranking

Para el proceso de admisión del año en curso, se acordó que los postulantes egresados de régimen regular de estudios secundarios, contarán con puntaje ranking, el cual expresa la posición relativa del alumno en el rendimiento de su colegio, tomando los promedios de los alumnos egresados de los años 2010, 2011 y 2012.

Los colegios que cuentan con menos de 30 alumnos egresados en la promoción del año, serán agrupados por ramas, con colegios de similares características para obtener su puntaje ranking.

Para los postulantes con exámenes libres, extranjeros, o egresados años del año 2009, se asignará como puntaje ranking igual valor que su puntaje NEM estandarizado.

A. 2013 Admission Process Guidelines

PARTE IV

PUNTAJE RANKING

El CRUCH en su Sesión Extraordinaria N°1, de 14 junio de 2012, incorporó a los factores de selección (puntaje NEM y los resultados de las pruebas PSU®), un nuevo factor, denominado Puntaje Ranking de Notas (acuerdo N° 24/2012).

El Puntaje Ranking expresa la posición relativa del alumno con referencia al rendimiento de su colegio, tomando los promedios de notas de los alumnos egresados del correspondiente establecimiento los años 2011, 2012 y 2013.

CÁLCULO DEL PUNTAJE RANKING

Para el cálculo del Puntaje Ranking se consideran dos valores característicos del establecimiento educacional del que egresa el postulante (independiente de su año de egreso). Estos dos valores característicos son:

1) Promedio de notas del colegio (N_C): para el cálculo del promedio de notas de cada establecimiento educacional se consideran los promedios anuales, por separado, de todos los egresados del establecimiento educacional de los años 2011, 2012 y 2013 (estos promedios son proporcionados por el MINEDUC). Luego, con estas tres notas se obtiene un nuevo promedio que sirve para determinar el Puntaje Ranking.

2) Promedio máximo de las notas del colegio (Max_C): para el cálculo del promedio máximo histórico de notas se considera el promedio de notas de egreso más alto de cada establecimiento educacional por cada año (2011, 2012 y 2013). Luego con estas tres notas se calcula el promedio máximo histórico de las notas del establecimiento educacional.

Ambos valores se calcularán con dos decimales sin aproximación.

El Ranking de Notas se calcula como una bonificación al puntaje NEM cuando el estudiante obtiene un promedio de notas superior al promedio histórico de su establecimiento educacional. Así:

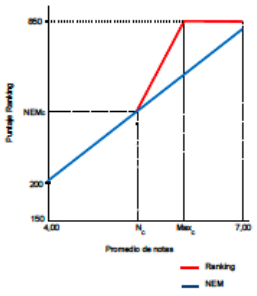
26

B. 2014 Admission Process Guidelines

- Los estudiantes con Notas de Enseñanza Media igual o inferior al promedio histórico de su establecimiento, obtienen un puntaje Ranking de Notas igual a su puntaje NEM.
- Los estudiantes con Notas de Enseñanza Media por sobre el promedio histórico de su establecimiento, obtienen un puntaje más alto. Este puntaje se calcula linealmente, con un máximo de 850 puntos cuando el promedio de notas iguala al promedio máximo histórico del establecimiento.
- Los estudiantes con Notas de Enseñanza Media por sobre el promedio máximo histórico de su establecimiento obtienen todos 850 puntos.

En la siguiente figura se grafica el procedimiento previamente descrito:

Puntaje Ranking CRUCH



C. 2014 Admission Process Guidelines: Graphical Explanation

FIGURE A26. Presentation of the Relative Ranking Score in the Official Admission Guidelines, 2013 and 2014 Processes

Note: This image reproduces the sections describing the relative ranking score in the official guidelines published by the centralized admission system for the 2013 and 2014 admission processes. Panel A shows the 2013 guidelines, where the ranking score is described in prose within Part II, "Normalización de las Pruebas", alongside the normalization of test scores. Panels B and C show the 2014 guidelines, where the ranking score appears as its own section, Part IV, "Puntaje Ranking". The 2014 version states separately how the score is computed for students below their school's historic average, between that average and the school's historic maximum, and above the maximum, and includes a figure plotting the ranking score against a student's grade average. The two documents can be dated from the school averages they reference: the 2013 guidelines use cohorts graduating in 2010, 2011 and 2012, and the 2014 guidelines use 2011, 2012 and 2013. The 2014 guidelines were released in 2014.

Appendix H. Grade Inflation and the Treatment Measures

This appendix reproduces the main results of Section 6.1 using treatment measures adjusted for grade inflation. The first part describes how the measures are reconstructed and reports a balance table comparing treated and control students before and after the adjustment. The second part reports the estimates of Equation 4 under each. Deflating the grades leaves them largely unchanged.

H.1. Constructing the grade-inflation-adjusted measures

To construct the adjusted measures, I use the results presented in Fajnzylber, Lara, and León (2019). They document that the ranking bonus raised recorded grades, and that it did so unevenly across schools in a form that schools whose students stood to gain more from grading leniently or had a high share of students on the "bonus" zone inflated more. Within schools, however, they find no evidence that inflation was targeted at the students with larger gains, pointing to schools raising grades uniformly across their own students but differentially across schools. Their estimates imply 0.164 grade points (in a scale 1.0 to 7.0) for cohort graduating in 2014, whose 10th, 11th, and 12th grades were affected, and they extrapolate 0.219 points once all four high school grades fall under the policy - roughly 0.055 points per exposed grade, and about twice that in the schools facing the strongest incentives.[47]

The treatment measures used in this paper are built from grades (see Section 4.3), so if grade inflation differs across schools it could change which students are recorded as having a potential gain or as having any gain at all. For inflation to confound the estimates it would have to be that (i) students are misclassified through changes in their own GPA and in the thresholds, so they count as treated only because inflation occurred, and (ii) switchers target schools that inflated less in the past, and so post lower thresholds, while expecting those schools to grade them no less generously than their origin school would have during the second semester, given the timing of switching (see Figure 8). Condition (i) alone would bias the estimates only if the resulting misclassification created non-classical measurement error; condition (ii) describes one of the behavior that would make that possible.

Following Fajnzylber, Lara, and León (2019), the first step in recovering the deflated inputs of the treatment measure, the student's GPA and high schools' thresholds, is to classify schools by the strength of their incentive to inflate. That strength has two parts: how much a marginal grade point is worth to a school's students, and how many of its students are positioned to use it. Let $\underline{r}_s$ be the mean GPA of school s over its three most recent graduating cohorts and $\bar{r}_s$ its highest performer across those cohorts, the two points in the GPA interval between which the ranking bonus rises. Then, a grade point inside that interval is worth

$$b_s = \frac{850 - z(\underline{r}_s)}{\bar{r}_s - \underline{r}_s} - z' \tag{A1}$$

[47] Grade inflation enters additively in their model, and it does so here.

points of ranking score, where $z(\cdot)$ is the national conversion from the GPA scale to the standardized score scale and z' its slope.[48] Letting π_s be the share of students in school s whose grades fall between the two thresholds, the school's incentive is $I_s = \pi_s \cdot b_s$. I compute I_s on the 2011 graduating cohort, the last one to finish high school before the policy was announced.

In a second step, I take the national distribution of I and sort schools into three groups: 737 schools place in the bottom quartile, 1,472 between the 25th percentile and the 75th percentile, and 736 in the top quartile. Four schools have no bonus zone, so I drop them. Students attending a school that cannot be matched to a 2011 value are assigned to the middle group; they account for 5.6 percent of student-years nationally over the period, and 5.5 percent of the estimation sample (Gran Santiago). Each group $g \in \{l, m, h\}$ is then assigned a rate of inflation per exposed grade δ_g, following the gradient in Fajnzylber, Lara, and León (2019).[49]

In the third step I deflate each input in turn: the students' GPA and the thresholds of their starting and ending school for those who switched. The three carry different amounts of inflation given how they are constructed. A student's GPA is the average of their four high school grades, and each year's grade is inflated only by what had accumulated by the year it was taken, so the average carries less than the final year alone. A school's thresholds are computed from its three previous graduating cohorts, so they carry the average of what those cohorts' own GPAs carried, which is less again.

TABLE A11. Exposure Multipliers for the Treatment Inputs, by Graduating Cohort

	Inflation carried, in units of δ_g	
Graduating cohort	Student's NEM	School's thresholds
2010	0.00	0.000
2011	0.00	0.000
2012	0.25	0.000
2013	0.75	0.083
2014	1.50	0.333
2015	2.50	0.833
2016	2.50	1.583
2017	2.50	2.167
2018	2.50	2.500

Note: This table presents the multiplier effect of grade inflation per cohort and input. Each entry is a multiplier, the same for all three incentive groups; multiply it by the school's own rate per exposed grade, δ_g, to get the grade points.

To fix ideas, take the cohort graduating in 2014 in a school in the middle group of incentives to inflate grades, therefore $\delta = 0.058$. Their four years of grade carry zero, one, two, and three units of δ_g respectively, so their GPA carries 1.50 δ_g or 0.087 points. The thresholds they face are built from the 2011, 2012, and 2013 graduates, whose own 4-year GPAs carried 0, 0.25 and 0.75 grades δ, so the

[48] Following DEMRE official information, the slope is 206 in the academic track, 202 for adult students in the academic track, and 204 for students in the vocational track.

[49] The gradient is 0.033 grade points per exposed grade in the low group, 0.058 in the middle group and 0.070 in the high group.

threshold carry 0.333 δ, or 0.019 points. Table A11 reports both multipliers for every cohort.[50]

Finally, with the deflated grades and thresholds, I recompute each student's potential gain at every school in their market exactly as in Section 4.3, and rebuild the discrete and the continuous measures. The two versions of the continuous measure correlate at 0.99. Of the 588,733 student-years in the estimation sample, 2.4% fall in a different treatment group under the adjusted measure: 0.8% acquire a positive potential gain, and 1.6% lose one, so the treated share falls from 38.1 to 37.3%. Reclassification is zero for the 2010 and 2011 cohorts by construction, reaches 4.0% in 2014 and peaks at 5.0% in 2015.

Table A12 reports means and standard deviations for students with and without a positive potential gain, computed first on the original data and then on the deflated data, together with the difference between the two. Grade point average is mechanically lower under the deflated data, by 0.075 points among students with no positive gain and 0.056 among those with one. Apart from it, the two groups look the same under both measures.

H.2. Main Switching Results under the Adjusted Measures

Figure A27 plots the estimates of Equation 4 under the original and the adjusted measures. Panel A presents the estimation coefficients using the discrete treatment measure, while Panel B presents the results under the continuous measure. In both panels circles report the estimates from the main text and triangles the estimates obtained after deflating grades and thresholds.

The two estimated coefficients track each other in every cohort. The 2014 estimate under the deflated discrete measure is 2.41 percentage points, against 2.48 in the main text, a fall of 2.6%. Under the deflated continuous measure the estimate is 1.41 against 1.47, a fall of 3.7%. The deflation (barely) moves the point estimate and leaves the standard errors unchanged to the third decimal.

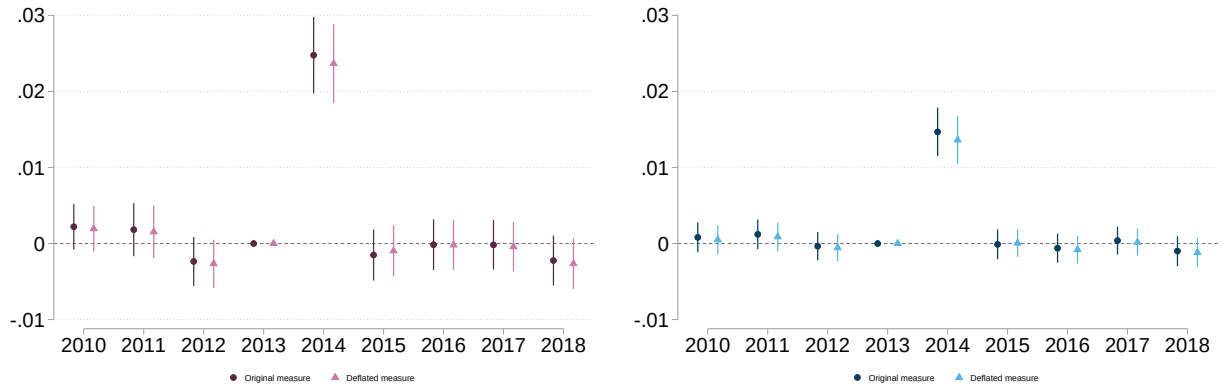
Back of the envelope calculations give a sense of how much inflation would be needed to account for the effect in full. What displaces a student across the gain boundary is not the level of inflation but the gap between what their own GPA carriers and what the thresholds they face carry, which for a middle-group school in the 2014 cohort is $(1.50 - 0.33).058 \approx 0.07$ grade points. That gap reclassifies 2.4 percent of the sample. Taking reclassification as locally proportional to the gap, accounting for the estimate in full would require reclassifying essentially the entire treated group, 38% of students, or roughly sixteen times the inflation Fajnzylber, Lara, and León (2019) document. That is a change of about 1.1 grade points, two and a half standard deviations of the GPA distribution, and would imply an average recorded GPA inflated from 5.5 to 6.6 on a scale that ends at 7.

[50] Deflated grades are censored below at 4.0, the minimum passing grade. The floor binds for at most two students in ten thousand in any cohort.

TABLE A12. Balance of Characteristics under the Original and the Deflated Discrete Treatment Measure

	Original measure				Deflated measure				Difference	
	No positive gain		Positive gain		No positive gain		Positive gain		No positive	Positive
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	gain	gain
Panel A: *Main dependent variables*										
Switch schools in 12th grade (beggining or during the AY)	0.05	0.22	0.03	0.16	0.05	0.22	0.03	0.16	-0.000	-0.000
Switch schools during the academic year	0.02	0.14	0.01	0.11	0.02	0.14	0.01	0.11	-0.000	-0.000
Panel B: *Characteristics (Used as Controls in decile bins)*										
GPA (non-standardized)	5.30	0.44	5.86	0.44	5.17	0.43	5.76	0.44	-0.135	-0.102
10th grade standardized score	-0.07	0.94	0.66	0.95	-0.06	0.93	0.68	0.95	0.002	0.017
Panel C: *Characteristics (Not Used as Controls)*										
Attending public schools	0.29	0.46	0.27	0.44	0.29	0.46	0.27	0.44	-0.001	0.001
Attending voucher schools	0.60	0.49	0.51	0.50	0.60	0.49	0.51	0.50	0.000	-0.003
Attending pricate schools	0.11	0.31	0.22	0.41	0.11	0.31	0.22	0.42	0.001	0.002
Attending national test prep. track	0.42	0.49	0.69	0.46	0.42	0.49	0.69	0.46	0.003	0.003
Attending vocational track	0.41	0.49	0.26	0.44	0.41	0.49	0.26	0.44	-0.002	-0.002
Atending Q1 schools	0.21	0.41	0.10	0.30	0.21	0.40	0.10	0.30	-0.001	-0.001
Atending Q2 schools	0.27	0.45	0.18	0.38	0.27	0.44	0.18	0.38	-0.002	0.001
Atending Q3 schools	0.27	0.45	0.26	0.44	0.27	0.45	0.26	0.44	0.000	-0.001
Atending Q4 schools	0.25	0.43	0.46	0.50	0.25	0.43	0.46	0.50	0.003	0.002
Mother education < HS	0.30	0.46	0.21	0.40	0.30	0.46	0.20	0.40	-0.001	-0.001
Mother education = HS	0.46	0.50	0.42	0.49	0.46	0.50	0.42	0.49	0.000	-0.002
Mother education > HS	0.24	0.43	0.37	0.48	0.24	0.43	0.37	0.48	0.001	0.003
Male	0.53	0.50	0.43	0.50	0.53	0.50	0.43	0.49	-0.001	-0.002
Female	0.47	0.50	0.57	0.50	0.47	0.50	0.57	0.49	0.001	0.002
Low aspirations	0.39	0.49	0.18	0.39	0.38	0.49	0.18	0.38	-0.002	-0.003
High aspirations	0.61	0.49	0.82	0.39	0.62	0.49	0.82	0.38	0.002	0.003
Does not have access to internet	0.24	0.43	0.17	0.37	0.24	0.43	0.16	0.37	-0.000	-0.001
Has access to internet	0.76	0.43	0.83	0.37	0.76	0.43	0.84	0.37	0.000	0.001
Observations	364,474		224,259		371,752		216,981			

Note: This table reports means and standard deviations of student and high school characteristics for students with and without a positive potential gain, under the treatment measure used in the paper and under a measure rebuilt from deflated grades. The deflation follows Fajnzylber, Lara, and León (2019). Columns (1) to (4) group students by the original measure and columns (5) to (8) by the deflated one. Columns (9) and (10) report the difference between the two, deflated minus original, for the no positive gain and the positive gain group respectively. Every characteristic is the same variable in both blocks, so a row differs only because the deflation reclassified students. Grade point average is the exception: the deflated block reports the deflated grade point average, so that row reflects the deflation of the variable as well as the reclassification. The sample is students observed in twelfth grade in the 2010 to 2018 graduating cohorts living in the Gran Santiago area during primary and secondary school.



A. Positive gain

B. Standardized gain

FIGURE A27. Switching Schools During 12th Grade, Original and Grade-Inflation-Adjusted Measures of Potential Gain

Note: This figure plots the interaction coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade. In Panel A the key regressors are the interactions between having a positive potential gain and event-year dummies; in Panel B they are the interactions between the student's median potential gain, standardized within their graduating cohort, and event-year dummies. In both panels, circles report the estimates obtained with the measure used in the paper and triangles the estimates obtained after deflating the student's GPA and the thresholds of every school in their market by the grade inflation implied by Fajnzylber, Lara, and León (2019). The sample consists of students living in Gran Santiago in primary school and in twelfth grade, and all coefficients are relative to 2013. The y-axis shows the change in the probability of switching relative to the omitted year; in Panel B this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the students' market level, and 99% confidence intervals are displayed.

Appendix I. Metropolitan Areas in Chile and the Conditions for Switching Schools

This appendix describes the school and college markets of Chile's metropolitan areas. The descriptive evidence from before the disclosure of the RR policy formula shows that areas differ in characteristics that make students more or less likely to switch: the school market determines whether a move is possible, and college markets whether it is worth making. Among the three main metropolitan areas, which together cover more than 50% of students in twelfth grade, only Gran Santiago meets both, and its scale is part of why: at nearly seven times the population of the next largest city, it has both more schools within reach and more selective programs to compete for.

Table A13 reports the population of each area and the size of its twelfth-grade cohort in 2013, the last cohort to graduate before the disclosure of the RR policy formula.[51] Gran Santiago is by far the biggest metropolitan area in the country, accounting for 39.5% of the nationwide population and 43.4% of twelfth graders. Gran Concepción and Gran Valparaíso, the next two largest areas in the country, hold roughly a million people each, representing 5.7% and 5.4% of the country respectively, while the fourth largest area, Gran Coquimbo, holds less than half a million people. The rest of the appendix presents characteristics for four groups: Gran Santiago, Gran Concepción, Gran Valparaíso, and the rest of the country.

TABLE A13. Population and Twelfth-Grade Students by Metropolitan Area

Metropolitan area	Population	Share (%)	Students in 12th grade	Share (%)
Gran Santiago	6,958,284	39.5	64,712	43.4
Gran Concepcion	1,008,512	5.7	9,190	6.2
Gran Valparaiso	952,990	5.4	8,640	5.8
Gran Coquimbo	432,786	2.5	3,715	2.5
Gran Rancagua	340,270	1.9	2,963	2.0
Gran Iquique	291,003	1.7	2,328	1.6
Gran Puerto Montt	284,465	1.6	2,108	1.4
Remaining areas	7,343,592	41.7	55,479	37.2
Total	17,611,902	100.0	149,135	100.0

Note: This table reports the average population and number of students observed in twelfth grade for each metropolitan area in 2013. Metropolitan areas are those defined by the government under Law No. 21.074. Population comes from INE's comuna-level projections, based on the 2017 census. Students are twelfth-graders assigned to an area if they live in that area during primary and secondary school, which is the sample definition used throughout the paper. Counties outside the seven areas are grouped as the rest of Chile. Each share is relative to the national totals.

[51] Metropolitan areas follow the government's definition under Law 21.074. Gran Santiago comprises Santiago, Cerrillos, Cerro Navia, Conchalí, El Bosque, Estación Central, Huechuraba, Independencia, La Cisterna, La Florida, La Granja, La Pintana, La Reina, Las Condes, Lo Barnechea, Lo Espejo, Lo Prado, Macul, Maipú, Ñuñoa, Pedro Aguirre Cerda, Peñalolén, Providencia, Pudahuel, Quilicura, Quinta Normal, Recoleta, Renca, San Joaquín, San Miguel, San Ramón, Vitacura, Puente Alto, Pirque, San José de Maipo, Colina, Lampa, Tiltil, San Bernardo, Buin, Calera de Tango, Paine, María Pinto, Talagante, El Monte, Isla de Maipo, Padre Hurtado and Peñaflor. Gran Valparaíso comprises Valparaíso, Viña del Mar, Concón, Quilpué and Villa Alemana. Gran Concepción comprises Concepción, Coronel, Chiguayante, Hualqui, Lota, Penco, San Pedro de la Paz, Santa Juana, Talcahuano, Tomé and Hualpén.

From the simple theoretical framework in Section 3, it follows that a student who wants to improve their ranking must (i) have at least one school within reach where moving would raise their score and (ii) be interested in programs that are selective enough for the change in the application score to be meaningful (see Equation 3).

Table A14 reports school market characteristics at three radii around each student's market centroid, defined as the geolocation of their primary school, by area group. Within 2 km a student in Gran Santiago has on average 18 alternative schools while a student in Gran Valparaíso has 17, and students in Gran Concepción and the rest of Chile have 10 alternative schools. The areas separate more as the market widens; at 6 km the counts are 111, 59, 30, and 20, respectively. The alternatives that would actually raise a student's ranking score follow the same pattern, rising from 7.4, 6.7, 4.1 and 3.8 at 2 km to 45.3, 22.4, 11.3 and 7.7 at 6 km for Gran Santiago, Gran Valparaíso, Gran Concepción, and the rest of Chile, respectively. When looking at the thresholds of the alternatives by school market, Gran Santiago has the lowest mean threshold at every radius, so a student with sufficiently good grades at a demanding school, whose own threshold is high, finds nearby schools whose distribution would place them higher; 41% of the alternatives at 2 km give a student a positive gain, and 39% of students have a positive median gain, the highest of all areas. The table also shows an important contrast between Gran Valparaíso and Gran Concepción: although Gran Valparaíso has many more schools within reach, they do not give students a meaningful median gain, 0.89 RR points against 5.43 in Gran Concepción.

TABLE A14. The School Alternatives and Potential Gains by Metropolitan Area

	Gran Santiago			Gran Concepción			Gran Valparaíso			Rest of Chile		
	2 km	4 km	6 km	**2 km**	4 km	6 km	**2 km**	4 km	6 km	**2 km**	4 km	6 km
Panel A: Size of the market												
Alternatives in market	**18.01**	56.77	111.49	**10.31**	19.42	29.99	**16.94**	39.97	58.99	**9.90**	17.18	20.26
Schools with positive gain	**7.37**	23.27	45.32	**4.10**	7.44	11.28	**6.67**	15.38	22.35	**3.83**	6.59	7.72
Panel B: Thresholds and gain												
Mean threshold in market	**5.44**	5.45	5.45	**5.56**	5.56	5.57	**5.55**	5.54	5.55	**5.52**	5.53	5.53
SD of threshold in market	**0.23**	0.24	0.25	**0.24**	0.25	0.26	**0.24**	0.26	0.26	**0.21**	0.22	0.22
Median gain	**4.87**	4.01	3.80	**5.43**	4.82	2.87	**0.89**	0.48	0.22	**4.99**	3.96	3.70
SD of median gain	**27.31**	26.42	26.44	**29.01**	27.93	26.64	**30.37**	29.07	28.86	**29.39**	28.28	28.25
Share with positive median gain	**0.39**	0.36	0.35	**0.38**	0.37	0.34	**0.31**	0.29	0.29	**0.36**	0.34	0.34
Number of markets		1,677			265			338			2,361	
Number of students		64,712			9,190			8,640			66,593	

Note: This table describes the mean of the outcomes that characterize a local school market at three radii, with the two-kilometer market used throughout the paper shown in bold. The sample is the graduating cohort of 2013, restricted to students who lived in the same metropolitan area during primary and secondary school. Each school has two thresholds that are relevant for calculating students' relative ranking (RR) scores: the mean and the maximum GPA of its three preceding cohorts. The mean thresholds reported here is the average, across the alternatives in a student's market, of those schools' mean thresholds, and the standard deviation is taken across students within the market. The median gain is the median across those alternatives of the increase in the student's ranking score had they graduated there, its standard deviation is also taken across students, and the share with a positive median gain is the fraction of students for whom the median gain exceeds zero. The last two rows report the number of distinct markets and the number of students in each area. Counties outside the three main metropolitan areas are grouped as the rest of Chile.

TABLE A15. College Programs and Applications by Metropolitan Area

	Gran Santiago	Gran Concepción	Gran Valparaíso	Rest of Chile
Panel A: *What is available*				
Number of programs (N=1,419)	475	175	210	559
Number of seats (N=110,380)	47,501	14,473	16,076	32,330
Share of seats left unfilled	0.07	0.18	0.12	0.22
Share of programs in the national top 100	0.14	0.06	0.05	0.02
Share of programs in the national top 500	0.53	0.33	0.34	0.22
Share of programs in the national top 1000	0.80	0.65	0.73	0.63
At least one campus from a tier 1 university (N=2)	2	0	0	1
At least one campus from a tier 2 university (N=3)	3	0	1	0
At least one campus from a tier 3 university (N=14)	8	3	3	7
At least one campus from a tier 4 university (N=14)	3	3	2	12
Panel B: *What students do*				
Share of students who apply in the same year they graduate	0.32	0.40	0.38	0.30
Among the first three preferences				
At least one program in own area	0.98	0.98	0.97	0.64
At least one program at a tier 1 university	0.47	0.05	0.09	0.15
At least one program at a tier 1–2 university	0.67	0.06	0.20	0.22
At least one program at a tier 1–3 university	0.90	0.85	0.88	0.81
Among the first five preferences				
At least one program in own area	0.99	0.98	0.98	0.69
At least one program at a tier 1 university	0.49	0.06	0.10	0.17
At least one program at a tier 1–2 university	0.71	0.07	0.22	0.25
At least one program at a tier 1–3 university	0.92	0.88	0.89	0.83
Number of students	64,712	9,190	8,640	66,593
Number of applicants	20,700	3,720	3,287	20,305

Note: This table describes the main characteristics of programs offered for the three main metropolitan areas and in the rest of the country. Panel A describes the programs offered in the 2014 admission process, the last process before the cohort affected by the RR formula disclosure applies. Programs are assigned to a metropolitan area by campus not headquarters. Numbers in parenthesis are national totals. The shares of programs in the national rankings are relative to the programs offered in each area. The national rankings order every program with at least one admitted student by the mean application score of those admitted. A program's seats are counted as unfilled when the number of accepted students is lower than the number of seats posted in the guidelines. The last four rows count universities with at least one campus in the area, so a university with campuses in more than one area is counted in each of them and these rows add up to more than the number of universities in the tier. Panel B describes the students who graduated from twelfth grade in 2013, restricted to those who lived in the same metropolitan area during primary and secondary school. A student is counted as applying if the application submitted in the same year they graduate is valid; a student who first applies in a later year is counted as not applying. The remaining rows are computed among applicants, separately for the first three and the first five preferences they list, and report the share listing at least one program of the stated kind. University selectivity tiers follow Kapor, Karnani, and Neilson (2024). Counties outside the three main metropolitan areas are grouped as the rest of Chile.

For a student to switch schools, alternatives with positive gain are worth having only if a better ranking changes the student's perception of where they can be admitted. Although the applications in the centralized system are at the national level, students apply extremely locally, so having selective programs in the area they live in is relevant. Table A15 describes the college market of each area. Panel A presents the characteristics of the programs offered in each area. Gran Santiago leaves only 7% of its seats unfilled, against 18% in Gran Concepción, 12% in Gran Valparaíso, and 22% in the rest of Chile. This is relevant because in a program that does not fill, every applicant is admitted and a better ranking changes nothing for those who apply to it. Notice that unfilled seats

in a program mean that the scores of its accepted pool of students are lower. Gran Santiago also offers far more that is worth competing for: 14% of the programs in Gran Santiago are among the hundred most selective in the country against 6% in Gran Concepción, 5% in Gran Valparaíso and 2% in the rest of Chile. If each area offered programs of similar selectivity, the share of their own programs in the top of the national ranking would be equal across areas. It is not, and the gap does not close as the group widens: at the top 1,000 of 1,419 programs, the share is 80% in Gran Santiago against 65% in Gran Concepción, and 73% in Gran Valparaíso.

Panel B shows how students respond to what their area offers. Among the first five preferences,[52] at least 98% of applicants list at least one program in their own area when living in one of the three main metropolitan areas. Their applications are not less ambitious when considering the first three of four tiers of universities, which is the highest tier where Gran Concepción and Gran Valparaíso have more presence.[53] The difference is at the top tiers: 71% of applicants in Gran Santiago list a program at a tier 1 or 2 university, against 22% in Gran Valparaíso and 7% in Gran Concepción.

[52] More than 95% of the applicants are accepted in one of their first five preferences (see Table 3).
[53] Valparaíso has one university in tier 2 with campuses in the Gran Valparaíso.

Appendix J. The Switching Response of Emblematic and Other High-Performing Public Schools

This appendix examines whether the switching response documented in Gran Santiago is concentrated among the public high schools commonly known as *liceos emblemáticos* (emblematic schools). I first define the category and identify the schools it contains, and how many high-performing public schools fall outside it. I then compare the university application patterns of students in the two groups before the policy, and finally estimate the response separately for each. I do not find evidence that the effects are driven only by emblematic schools.

Emblematic schools in Chile. They are long-established public high schools associated with academic excellence, tradition and prestige. The Ministry of Education recognizes no single definition of the category and has produced at least two lists that do not entirely coincide. The first, in a 2020 Centro de Estudios report, names 19 schools, all in the metropolitan region of Santiago. The second, the 2025 Plan de Recuperación de Liceos Emblemáticos, names 28 schools across the country. They overlap on 9 schools, so I use their union, which is a total of 38 schools, throughout this appendix. Table A16 lists them and reports which list each appears on. Fifteen of the 38 schools lie outside Gran Santiago, so the category is not specific to the main metropolitan area.

Within Gran Santiago, the emblematic schools are a subset of high-performing public schools: among the 45 public schools considered high performing, 18 carry an emblematic designation, and 27 are not considered emblematic schools. Comparing the two categories holds performance and financing fixed, so a difference between the two sets reflects the designation and other characteristics correlated with it.

One such characteristic is whether their students apply to university at all, and where they aim when they do. Among the cohorts graduating from high school between 2010 and 2011, 62.1% of students at the emblematic schools submitted a valid application, against 25.2% at the other top-quartile public schools; among those who applied, 82.1% listed a program at a tier 1 or 2 university among their first five preferences, against 64.8% (see Table A17). A student who was already directing applications at the most selective universities is a student for whom an increase in the ranking score may seem more important, and who may therefore be more likely to switch.

Figure A28 presents the results for each type of high-performing public school separately. Students with a positive median gain at the 27 non-emblematic schools increase their probability of switching in 2014 by 7.41 pp, and students at the 18 emblematic schools by 13.85 pp. Estimating the two jointly produces a difference of 6.44 pp which is statistically significant at the 1% level. Under the continuous measure the estimates are 4.15 pp and 6.85 pp with a difference of 2.70 pp at the 5% significance level. Students attending emblematic schools respond more than any other group in the analysis, but they are not driving the results; students in other high-performing public schools with positive potential gain also react to the policy formula disclosure.

The separation appears only once the formula is public. Taking 2012 as the omitted year, the emblematic differential is 0.71 pp in 2013, not distinguishable from zero, against 14.44 pp in 2014;

TABLE A16. Schools Identified as *Liceos Emblemáticos*

School	Comuna	Region	2020 list	2025–26 plan
Metropolitan Region(Santiago)				
Instituto Nacional	Santiago	Metropolitana	•	•
Javiera Carrera	Santiago	Metropolitana	•	•
Isaura Dinator de Guzmán	Santiago	Metropolitana	•	•
Liceo de Aplicación Rector Jorge E. Schneider	Santiago	Metropolitana	•	•
Manuel Barros Borgoño	Santiago	Metropolitana	•	•
Internado Nacional Barros Arana	Santiago	Metropolitana	•	•
Miguel Luis Amunátegui	Santiago	Metropolitana	•	
Confederación Suiza	Santiago	Metropolitana	•	
Darío Salas	Santiago	Metropolitana	•	
Miguel de Cervantes y Saavedra	Santiago	Metropolitana	•	
Teresa Prats	Santiago	Metropolitana		•
Valentín Letelier	Recoleta	Metropolitana	•	
Liceo N° 7 Luisa Saavedra de González	Providencia	Metropolitana	•	•
Carmela Carvajal de Prat	Providencia	Metropolitana	•	•
José Victorino Lastarria	Providencia	Metropolitana	•	•
Polivalente Arturo Alessandri P.	Providencia	Metropolitana	•	
Tajamar	Providencia	Metropolitana	•	
Carmela Silva Donoso	Ñuñoa	Metropolitana	•	
República de Siria	Ñuñoa	Metropolitana		•
Augusto D'Halmar	Ñuñoa	Metropolitana		•
José Toribio Medina	Ñuñoa	Metropolitana		•
Andrés Bello	San Miguel	Metropolitana	•	
Instituto Superior de Comercio de Chile	San Miguel	Metropolitana	•	
Outside the Metropolitan Region				
Octavio Palma Pérez	Arica	Arica y Parinacota		•
Bernardo O'Higgins	Iquique	Tarapacá		•
Mario Bahamondes Silva	Antofagasta	Antofagasta		•
José Antonio Carvajal	Copiapó	Atacama		•
Gregorio Cordovez	La Serena	Coquimbo		•
Eduardo de la Barra	Valparaíso	Valparaíso		•
Óscar Castro	Rancagua	O'Higgins		•
Abate Molina	Talca	Maule		•
Narciso Tondreau	Chillán	Ñuble		•
Enrique Molina Garmendia	Concepción	Biobío		•
Pablo Neruda	Temuco	La Araucanía		•
Armando Robles Rivera	Valdivia	Los Ríos		•
Manuel Montt	Puerto Montt	Los Lagos		•
Josefina Aguirre Montenegro	Coyhaique	Aysén		•
Luis Alberto Barrera	Punta Arenas	Magallanes		•

Note: This table lists the schools identified as *liceos emblemáticos*. The category has no single official definition, and the Ministry of Education has produced at least two lists that do not entirely coincide. The first is MINEDUC, Centro de Estudios, *Apuntes* 1-2020, Table A1, which reproduces a 2016 list and covers the metropolitan region of Santiago only, so its coverage is a feature of the source rather than evidence that no comparable schools exist elsewhere. The second is the Plan de Recuperación de Liceos Emblemáticos, ministerial resolution of 3 March 2025, comprising the 19 schools entering the plan in 2025 and the 9 entering in 2026. The last two columns record which of the two sources names each school. Nine schools appear on both, so the analysis uses their union, 38 schools. Schools are grouped by whether the school itself is located in Gran Santiago, which is the same criterion used to define the estimation sample.

under the continuous measure it is 0.14 pp and 6.75 pp. In the year in which a school with advance knowledge of the formula could have acted on it, these schools moved no more than any other.

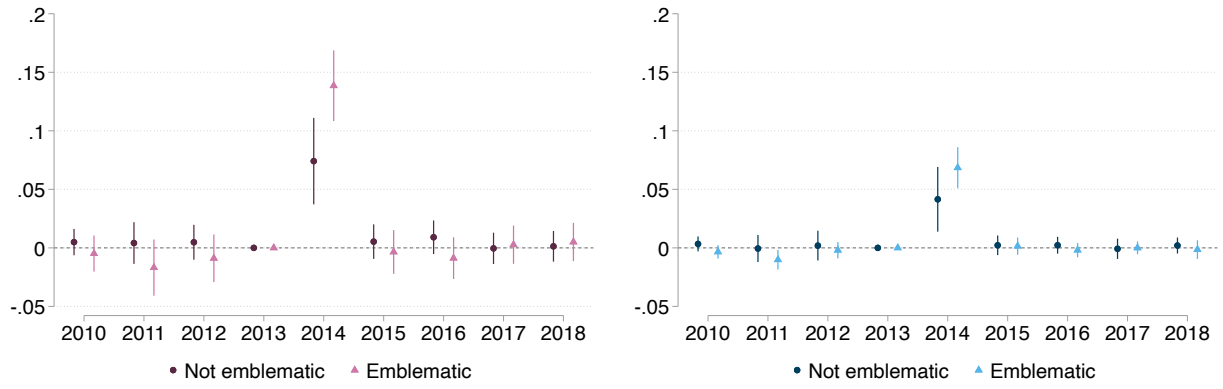
Because the estimates compare students in the same school and the same GPA decile who differ in whether their own market offers a gain, a school that informed all of its students is captured

within these fixed effects. However, what the design used in the paper cannot separate is the channel through which the information reached students, which may have included teachers or peers in the schools. That would bear on the estimates only if schools acted differently toward different students, and the response schools are documented to have made in this setting is grade inflation applied homogeneously across their own distribution (Appendix H), which reduces the concern that the response reflects schools behaving strategically rather than students reacting to the policy.

TABLE A17. University Applications Before the Policy, Emblematic and Other High-Performing Public Schools

	Share applying to university (%)	Share listing a tier 1 or 2 university in the first five preferences (%)	Students	Applicants	Schools
Emblematic	62.1	82.1	7,721	4,797	18
Not emblematic	25.2	64.8	5,666	1,430	26
Difference	36.9	17.3			
	(8.1)	(5.7)			
p-value	<0.001	0.004			

Note: This table describes the application patterns by students who graduated from twelfth grade between 2010 and 2011, the last cohorts to apply before the RR policy was announced. The sample is restricted to students living in Gran Santiago in primary school and in twelfth grade who attend a school located in Gran Santiago that is public and in the top quartile of the regional performance distribution. A student is counted as applying if the application submitted in the same year they graduated is valid. The second column is computed among applicants and reports the share listing a program at a tier 1 or 2 university among their first five preferences. University selectivity tiers follow Kapor, Karnani, and Neilson (2024). A school is counted as emblematic if it appears on either of the two lists reported in Table A16. The estimation sample contains 45 schools, 18 emblematic and 27 not (all in Gran Santiago). Each difference is estimated by regressing the indicator on the emblematic designation, with standard errors clustered at the school level and reported in parentheses.



A. Positive gain

B. Standardized gain

FIGURE A28. Switching Schools During 12th Grade, Emblematic and Other High-Performing Public Schools

Note: This figure plots the interaction coefficients from estimating equation (4), where the outcome is an indicator for switching schools in twelfth grade. In Panel A the key regressors are the interactions between having a positive potential gain and event-year dummies; in Panel B they are the interactions between the student's median potential gain, standardized within their graduating cohort, and event-year dummies. In both panels, circles report the estimates for schools without an emblematic designation and triangles the estimates for emblematic schools, each set estimated separately. The sample consists of students living in Gran Santiago in primary school and in twelfth grade who attend a school located in Gran Santiago that is public and in the top quartile of the regional performance distribution: 45 schools, of which 27 carry no emblematic designation and 18 do. A school is counted as emblematic if it appears on either of the two lists reported in Table A16. All coefficients are relative to 2013. The y-axis shows the change in the probability of switching relative to the omitted year; in Panel B this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the students' market level, and 99% confidence intervals are displayed.

Appendix K. Construction of the Higher-Education Outcomes

This appendix describes how the higher-education outcomes used in Section 6 are built, and the characteristics used to describe the programs students apply to, enroll in, and graduate from. It also reports descriptive statistics on those characteristics.

K.1. From the Admission Process to the Degree

From the administrative data sources described in Section 4, I use the Servicio de Información de Educación Superior of the Ministry of Education (SIES) and the Departamento de Evaluación, Medición y Registro Educacional (DEMRE) datasets to construct the higher-education outcomes.

From DEMRE, I obtain the national university admission test (PSU) registration, the rank-ordered list (ROL) of program-university pairs, the preference into which they were admitted, for every admission process, and ultimately the program in which they enrolled if they used the regular process,[54] and the program catalogue with each program's admission weights. From SIES, I obtain the yearly enrollment panel of every student in higher education, the yearly file of degrees awarded, and the average earnings and employability statistics aggregated by generic field within university.[55] Throughout the analysis, I keep students who graduated from high school between 2011 and 2016 (see Section 6 for the definition of the sample) and follow them until they graduate from college or until academic year 2025-2026, the last academic year available in SIES public records.

Since students can apply more than once through the centralized system after they graduate from high school, either with the same PSU score or by retaking the test, I create the outcomes at the student-process level first, and then at the student level. A process is a PSU sitting, or, for a student who applies and enrolls using a PSU score from an earlier process, the year they enroll.[56] Each student-process carries whether the student applied, the programs on their list, whether and where they were admitted, the program they enrolled in, and any program they moved into afterwards without a break of more than one year. For students observed in more than one process, a degree is matched to the process whose programs it came from.

I create a student pipeline in higher education as follows: I take students graduating from high school between 2011 and 2016, and look at all the university admission processes available to them. For a student graduating from high school in cohort $t \in \{2011, \ldots, 2016\}$ I look at PSU sittings for admission processes $t+1$ to T, where $T = 2020$, the last process available in the data. For applications, acceptances and enrollments I do the same over admission processes $t+1$ to T. For dropout and switching out of the program they first enrolled in, I use the yearly enrollment

[54] The centralized system has a few additional routes through which a student can be admitted to a university; all require the PSU, but some, such as PACE, admit students through a different process.

[55] The DEMRE catalogue lists 1,419 programs in the 2014 admission process, while SIES records 1,851 programs in Table 1 once campus and non-centralized programs, mostly evening programs, are considered. Earnings are published for 800 university-generic-field cells, so programs at the same university in the same generic field share one figure.

[56] 458 students are dropped from the sample since they first enrollment is not preceded by a PSU sitting in the data.

panel to build the spell. Finally, for graduation, I use the degrees conferred each year and compare the program students graduated from with the program they first enrolled in.

K.2. Outcome Variable Definitions

I start by defining a variable equal to one if the student sat the PSU in the year they finish high school and zero otherwise. I create similar dummies for sitting it for the first time at least one year later, and for application, acceptance, enrollment and graduation at a higher education institution that uses the centralized system to allocate its slots. Additionally, I estimate the same set of results by university and program characteristics. I create dummies equal to one if students applied to, were accepted into, enrolled in, or graduated from a program that is either at a tier 1 or tier 2 university, is highly selective, high-return, traditional, or STEM. For applications I focus on programs listed among the first three preferences. I also create dummies for leaving the program, and split it into switching programs and dropping out of the centralized system. Throughout the paper, not enrolling in a university in the centralized system does not distinguish between enrolling in a higher education institution outside the centralized system and joining the labor market after high school. The results for this set of outcomes are presented in Section 6.

Two additional rules apply to the variable definitions. First, an enrollment counts only if the program was in the DEMRE offer in the year the student entered it; this excludes programs at universities using the system that are evening, distance, or special plans for people who already hold a degree. For universities that joined the centralized system during the period of analysis, enrollments before the institution started using the system are not considered. Second, a common-entry program –plan común, bachillerato or ingreso común– and the degree it feeds are considered one program. Graduation on time compares the semesters from entry to the title against the program's nominal study and titling length.

K.3. Program Characteristic Definitions

The centralized system offered a total of 1,673 programs between the 2012 and 2017 admission processes. For the analysis I fix program characteristics at a period before the disclosure of the policy. For university selectivity, I follow Kapor, Karnani, and Neilson (2024) and classify universities across 4 tiers using the 2012 admission process. For program selectivity, I use the 2014 admission process, which contains 1,333 of the 1,423 programs offered in the 2015 admission process, the first to which students exposed to the policy disclosure could apply. Selectivity is calculated using the average score of the admitted students. A program is categorized as highly selective if belongs the highest quartile of programs' average scores.

For program returns, I use the mean monthly income of the program's graduates in the fourth year after the degree conferral, calculated by SIES pooling the 2013, 2014 and 2015 university graduating cohorts.[57] For programs in the 2014 DEMRE catalogue without earnings information,

[57] A student exposed to the disclosure finishes high school in 2014 at the earliest, enters college in 2015, and cannot

either because the cohorts are too small and SIES suppresses the cells, or because the figure was not reported, earnings are predicted from a linear model with graduation-year, generic-field and university fixed effects. Of the 1,419 programs in the 2014 admission process, 744 have a reported figure, 547 a predicted one, 45 the mean of the degrees they feed (plan común, bachillerato and ingreso común), and 83 none. A program is considered high-return if it belongs to the highest quartile of average income. Finally for the last two classifications, STEM and traditional, I use the field classifications SIES assigns to each program. A program is STEM if SIES classifies it in the natural sciences, mathematics and statistics, engineering, or information technology fields of the CINE 2013 classification, and traditional if its generic field is business administration, medicine, law, or civil engineering. From the 1,419 programs offered in the 2014 admission process, 14.2% are at a tier 1 or 2 university, 24.1% are highly selective, 26.5% are high-return, 17.4% traditional and 32.1% STEM.

hold a degree before 2019, so none appears among the college graduates the figure is built from.

Appendix L. The 2011 Student Protests and Their Effect on School Switching

In this appendix I describe the shock that increased school switching in twelfth grade in Chile and present evidence that helps differentiate the strategic changes in 2014 from the responses to the protests in 2011.

Starting in May 2011 and continuing until the end of the year, Chilean secondary school and higher education students staged protests and school occupations that could last from hours to months (UNICEF Chile 2014; Penaglia and Mejías 2019). The protests sought to express the students' opposition to the prevailing funding and governance of the education system (Somma 2012). By June 2011 466 schools were occupied (Penaglia and Mejías 2019), with the occupations concentrated in public schools, although voucher and private schools were occupied as well (UNICEF Chile 2014). Although the mobilizations were concentrated in Santiago, of the 124 days of protest recorded in 2011, 52 were simultaneous in Santiago and other regions, 47 in Santiago alone and 25 in other regions (Penaglia and Mejías 2019).

There are two main aspects that separate the 2011 and 2014 moves in twelfth grade and their underlying motives:

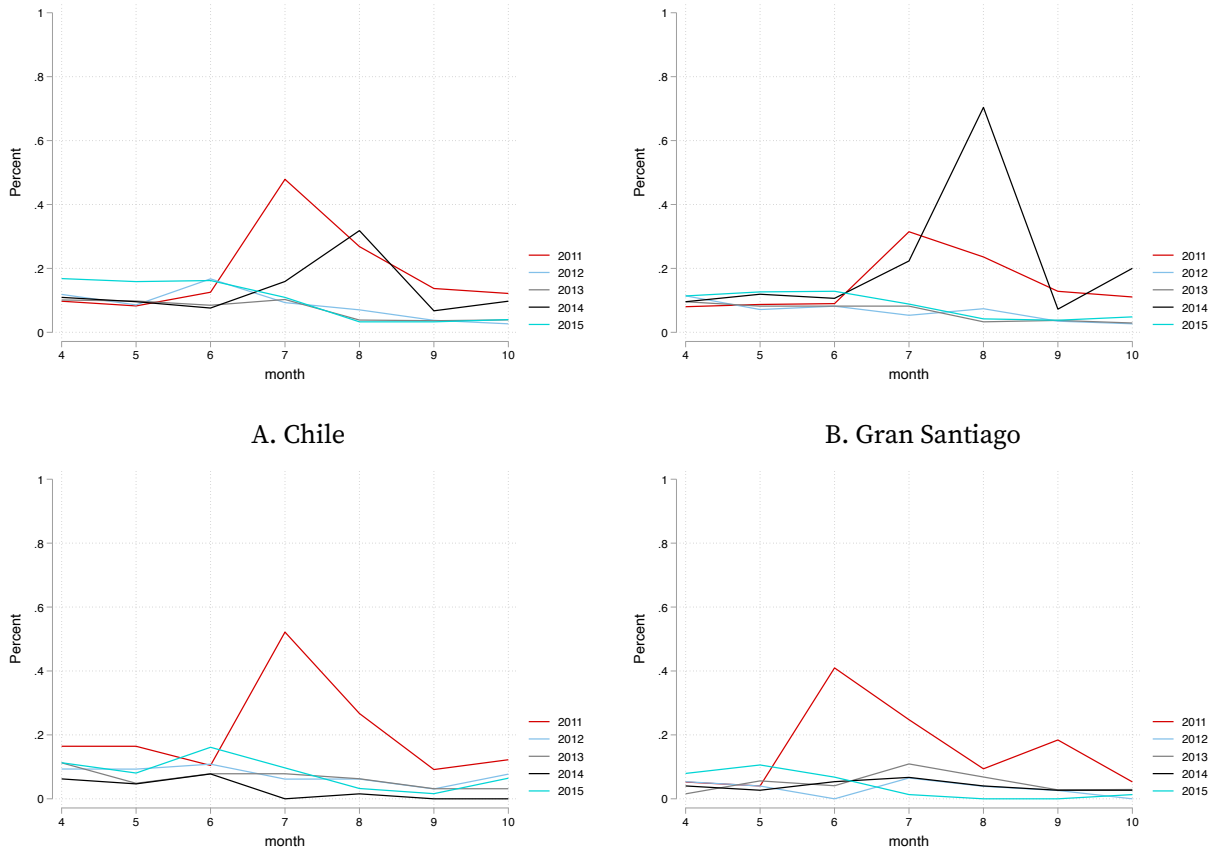
Timing. In general, the changes produced by the 2011 protests were more pronounced right after the occupations started between May and June 2011.[58] Figure 5 shows the trend in changes across years, dividing switches into those at the beginning of the year and those during the year. The pattern confirms that school switching in 2011 were connected with the protests. First, in the full country the number of changes during the year spikes in 2011, while the number of changes at the beginning of the year peaks in 2012, which suggests students change schools for the academic year right after the 2011 protests. Second, the monthly changes confirm that students switched schools earlier in the year in 2011 than in 2014: the monthly probability of changing school peaks in July 2011 and in August 2014. Finally, the event study comparing students who stood to gain with students who did not have gains shows that *treated* students switched more in July during 2011 (Figure A30), the month after the protests and occupations started, while they did so mostly in August in 2014 (Figure 8). Additionally, students with a potential gain changed more than students with no gain in 2011, but by less than in 2014, suggesting the 2011 shock affected all students in schools that participated in the protests (Figure 8).

Geography. The protests in 2011 were concentrated in Gran Santiago but extended to the whole country by June 2011. Gran Concepción and Gran Valparaíso were two other metropolitan areas heavily affected by them; the most affected counties, however, were spread across the whole country. Figure A29 shows that these two metropolitan areas saw a substantial switching in 2011 but not in 2014. I discuss the reasons why there is no spike in 2014 in Gran Concepción and Gran Valparaíso in Appendix I. To separate the counties most affected by the protests and occupations I use newspaper coverage to build a list of the thirty most affected counties in 2011,[59] and split the

[58] Emol, 13 June 2011, reports close to one hundred schools occupied across the country.

[59] The thirty counties are Concepción, Valparaíso, Punta Arenas, Antofagasta, Calama, Temuco, Valdivia, Arica, La Serena, Iquique, Rancagua, Talca, Puerto Montt, Viña del Mar, Coquimbo, San Antonio, Talcahuano, Curicó, Osorno,

country outside Gran Santiago between those counties and the remainder. The July 2011 increase appears only in the affected counties: it is there that students with a positive potential gain are more likely to change schools inn July 2011 than in March 2013, while in the rest of the country the same difference is not distinguishable from zero. Reassuringly, the pattern using the continuous measure is the same (Figure A30).



A. Chile

B. Gran Santiago

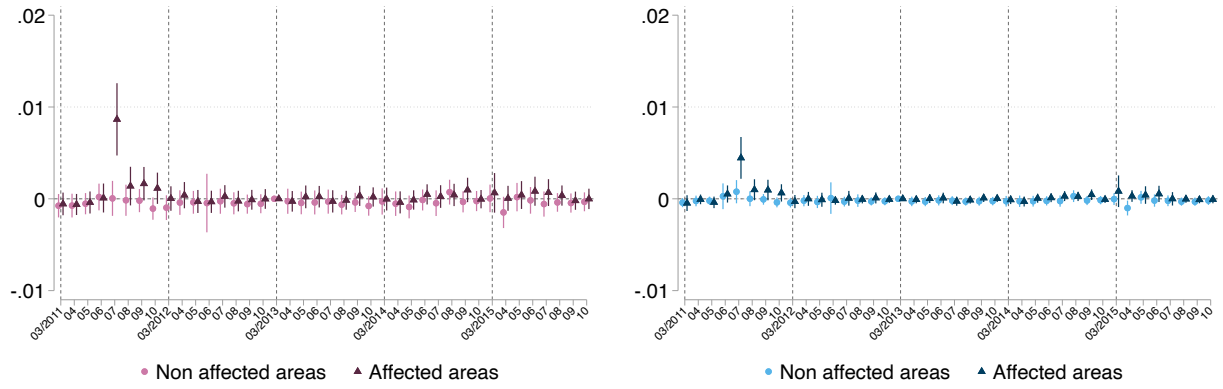
C. Gran Valparaiso

D. Gran Concepción

FIGURE A29. Percent of Students Switching Schools in Twelfth Grade (2010-2018)

Note: Each panel reports the percent of twelfth-grade students who change school in each month from April to October, with one line per year. The academic year in Chile runs between March and mid-December of each calendar year. A student is counted as switching in a given month when the school recorded in the following month differs from the school recorded in that month; the denominator is all twelfth-grade students enrolled in that month. Panel (a) covers the whole country. Panels (b) to (d) restrict the sample to students whose primary school, twelfth-grade school of origin and school of attendance all lie in the metropolitan area named in the panel.

Chillán, Copiapó, Coronel, Los Ángeles, Quillota, Tocopilla, San Felipe, Linares, Ancud, Coyhaique and Ovalle. A student is assigned to the affected group when the comuna of the primary school, the county of the twelfth-grade school and the county of the school attended in the month of observation all belong to this list. The comparison group is the remaining 248 counties outside Gran Santiago, together with the students of the thirty affected counties whose primary or twelfth-grade school lies outside them.



A. Positive gain

B. Standardized gain

FIGURE A30. Monthly School Switching During 12th Grade Outside Gran Santiago

Note: This figure plots the interaction coefficients from estimating equation (4) at the month level, where the outcome equals one in the last month the student is observed at their original school in twelfth grade before moving to a different school, and zero in every other month. In Panel A the key regressors are the interactions between having a positive potential gain and month dummies; in Panel B they are the interactions between the student's median potential gain, standardized within their graduating cohort, and month dummies. In both panels, circles report the estimates for the remaining counties outside Gran Santiago and triangles the estimates for the thirty counties most affected by the 2011 protests, listed in footnote 59, each group estimated separately. The sample consists of students whose primary school, twelfth-grade school of origin and school of attendance all lie outside Gran Santiago. All specifications include twelfth-grade school of origin and within-school GPA decile fixed effects. All coefficients are relative to March 2013. The y-axis shows the change in the probability, on a scale 0 to 1, of switching in a given month relative to the omitted month; in Panel B this is the change associated with a one standard deviation higher potential gain. Standard errors are clustered at the students' market level, and 99% confidence intervals are displayed.