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

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(Job Market Paper)

December 29, 2022

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Abstract

Policies aimed at increasing the number of students from underrepresented groups in college are common worldwide. Yet, little is known of their unintended pre-college effects or if these effects are aligned with the intended goals of the policy. This paper asks whether centralized college admission policies that rank students within their high school lead to students making strategic moves in high school and how those moves affect the policy's impact. Relying on a policy change in Chile that intended to address the issue of lower socioeconomic status students attending college and using detailed administrative data and a simple theoretical model, I show that high school students reacted to this relative ranking admission policy by switching schools, undermining the policy's effectiveness. I find that the number of low-income students accepted into top colleges increased by less than 1 percent under the current policy, but if students were not allowed to switch high schools, that increase would be 5 percent. I argue that schools switching is an important pre-college response, which needs to be considered when designing college admission policies dependent on attended high school, as it can undermine said policies.

*I am extremely grateful to Garance Genicot, Laurent Bouton and Christopher Neilson for continuous encouragement, help, and suggestions, their guidance and support are invaluable. I am very thankful to Mary Ann Bronson, Cauê Dobbin, and Jishnu Das for all their insights and suggestions in the process of this paper. I thank Gaurav Bagwe, Paul Treadgold, Nieves Valdés, Maria Hernandez de Benito, Allison Stashko, and Sebastian Otero for their comments on the latest drafts. I also thank all the mentors at CSWEP for their wonderful comments. I have also benefited from fruitful discussions with several seminar speakers and colleagues at Georgetown University. All errors are my own, and the usual caveats apply.

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1 Introduction

The limited college access for disadvantaged students has long been a concern among academics and policymakers worldwide.[1] However, the division between rich and poor in terms of attendance continues. In Latin America, for example, the ratio of total enrollment in higher education from the poorest quintile of the population was ten percent in 2018, more than fifty percentage points lower than the wealthiest quintile (UNESCO, 2020). Increasing opportunities for students from historically disadvantaged populations and communities have been the focus of many different policies.[2] Such policies have been found to have the potential to increase a country's social mobility without efficiency loss, contribute to equalizing opportunities and increase redistribution of college attendance without distortions (Bleemer, 2020; Chetty et al., 2020; Estevan et al., 2019; Otero et al., 2021; Melo, 2021; Black et al., 2020; Kapor, 2015).

A popular policy to alleviate inequality in college access – but also a very controversial one — is the special consideration of certain groups in college acceptance, known as affirmative action (see Arcidiacono et al. 2015).[3] One important challenge when using affirmative action or similar policies addressing inequality in access to college is the response from those who are not included in the policy and who often see themselves as being disadvantaged by it. This can lead to public outcry, legal challenges, and individual students trying to game the system to their own advantage.[4] Despite the increasing popularity of affirmative action, evidence of how such

[1] Although the gross worldwide college enrollment rate increased from 19% to 38% between 2018 and 2020, enrollment is still concentrated in the wealthier social stratas (UNESCO).

[2] Policies vary from special consideration to a given group during the application process; positive discrimination or quotas (Otero et al., 2021; Antonovics and Backes, 2014; Kapor, 2015); financial aid (Solis, 2017; Burland et al., 2022); to simply providing information about how to apply to college, the benefits from attending college, and aid around college loan repayments (Cox et al., 2020); or reducing uncertainty about college requirements and returns to tertiary education (Dynarski et al., 2021). See Deming and Dynarski (2010) for a comprehensive analysis of types of programs reducing college costs and their effectiveness.

[3] About one-quarter of countries across the world use some form of affirmative action (Jenkins and Moses, 2017) to increase the representation of historically disadvantaged populations and communities in higher education. Some examples are Texas, where the top 10% of students (by GPA) from each high school can attend any public university in Texas of their choice (Antonovics and Backes, 2014; Kapor, 2015); Brazil, where federal universities implemented quota laws (Melo, 2021; Mello, 2020); and Chile, which incorporated a measure to compare a given student's GPA to historical trends in their high school (Larroucau et al., 2015; Reyes, 2022)

[4] In the US, the Supreme Court has recognized that colleges and universities have a valid educational interest in attracting and having a diverse student body (see Regents of the Univ. of California v. Bakke (1978), Grutter v. Bollinger (2003), and Fisher v. Univ. of Texas (2016)). However, they heard the arguments in the SFFA v. Harvard University case at the end of October

policies affect high school choice is limited (Cullen et al., 2013; Mello, 2021; Estevan et al., 2018).

In this paper, I study how Chilean high school students respond to one such college admission policy and whether their responses have unintended consequences with respect to the policy goals. I leverage the 2014 release of information about a new criterion added to the application score in the centralized college admission process in 2012.[5] This score was previously solely based on students' high school grade point average (GPA) and a standardized test score. From 2012 onwards, the college application score includes additionally a new measure based on students' relative high school performance (relative ranking or RR), which compares a student's GPA to the mean of the three previous cohorts in their school. This new component's formula and comparison group create incentives for students to switch high schools from schools that they have chosen based on educational quality and/or personal factors to schools that allow them to maximize their relative ranking and, thus, their probability of being admitted to their chosen college.

Chile is an interesting setting for this analysis for several reasons. First, a major challenge in studying policies addressing unequal access to college and students' strategic responses is the lack of detailed records that combine primary and secondary school data, students' application portfolios, and their pre-college decisions. Chile has extensive detailed administrative data at the student level on primary and secondary education and during the college application process, overcoming this problem (Bodoh-Creed and Hickman, 2018). Second, Chile has a centralized system, with clear and simple admission rules, an application score formula, and applicants' preferences over major and college combination (*degree*),[6] which helps researchers to calculate the matches between students and majors under different circumstances for the entire system.[7]

For this paper, I create a unique data set to characterize the students who are switching high schools due to the policy and the impacts of these decisions on several outcomes of interest, such as the college acceptance rate by students' socioeconomic

2022, where SFFA seeks to ban Harvard's race-conscious admissions. An unusual aspect of this case is the claim that affirmative action hurts Asian-American students, even though they are members of a disadvantaged group.

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

[6]Students apply in advance to specific degrees, e.g., to Economics at the University of Chile.

[7]This type of admission system is becoming more popular worldwide; the number of countries using centralized admission for college admission has more than doubled since the nineties (Neilson, 2019). Making the results in this paper broadly relevant.

backgrounds. First, I combine several administrative records containing student characteristics, including their yearly GPA and type of school attended (public, private, and voucher) during K-12. Second, I merge these records with the information from the college admission system that contains students' performance on the national university entrance exam (PSU), socioeconomic characteristics, application portfolios, and college admission offers, among other factors. Finally, I incorporate information from a paired standardized test and survey taken in tenth grade (SIMCE) that contains both the test scores and parental answers to several questions about students' household characteristics. Equipped with these data, my analysis shows that students' behavioral responses during high school to the Chilean RR policy substantially reduce the effect of increasing college acceptance for disadvantaged students.

In the first part of the paper, I exploit the simple application score formula and the college-student matching algorithm to study the policy's effects. Here, I also develop a discrete choice model to connect students' decisions to switch schools with the policy results. To evaluate the policy, I calculate what would be the students/majors allocation if no one switched schools in grade 12 with the matches we observe after some students behave strategically. When considering school performance, I find that students from low-performing schools are 8% more likely to be accepted into selective colleges. However, if no student switched schools, the effect of the policy could be as high as 12%, a potential effectiveness drop of more than 30%. Now, when considering students' socioeconomic status (SES) instead, I find that the increase in the number of students from low-income (low-SES) families accepted in selective colleges would have been about 5% if students did not switch schools, while the effect is around 0.5% when considering switching. When students are allowed to switch schools, my results are consistent with the government's independent policy evaluation (Larroucau et al., 2015).

Now, how do students' decisions to switch high schools and policy effectiveness connect theoretically? The answer is unclear, especially if the potential increases in college application scores by switching are distributed similarly among all students in the system. To better understand the connection, I build a simple school choice model where students decide whether to switch high schools while taking the selective colleges' application cutoff as a given. This model has three main insights. First, the effect of the policy, specifically changes in the acceptance pool, depends on the costs of switching high schools to students. When the relocation cost is high, the policy is more successful in increasing the acceptance rate for low-performing schools.[8] Second, given the relative ranking formula, not all students have incentives to switch schools, even when the relocation cost is small. Third, students in high-performing schools are the most likely to benefit from switching high schools since those schools have higher GPA thresholds.

The second part of my paper then identifies which students could increase their application scores by switching schools and how many of those students took advantage of the policy. To evaluate the application score changes due to school switching, I take advantage of when the RR policy information was released, its clear rules, and the students' relevant schools.[9] I calculate each student's application score for all schools they could switch to. I then take the highest score increase they could have (*potential gain*). Using this variable, I show that: (i) the realized and potential gains are positively correlated, although students did not actually receive the maximum increase when switching schools, and (ii) not all the students who could have profited from switching actually did (on average, 3 percent of students with high potential gain switched schools), highlighting students' heterogeneities among switching cost, the value of the high school and college attended.

Given that not all students could benefit from switching, I characterize students who actually switched schools once the RR information was public, i.e., in 2014, and compare them with students switching schools in 2013 and 2012. To do so, I calculate students' application score gain for all the cohorts, e.g., 2012 to 2014. Using a difference-in-difference design, I exploit the variation between cohorts and students' predetermined characteristics to show that, within schools, students from high SES backgrounds and with high aspirations[10] increase their likelihood of switching schools by 0.8 percentage points or 36% – relative to a 2.2 percent base probability —. Further, students starting the academic year in high-performing or public schools were more likely to switch post-policy.

Finally, motivated by my previous findings and taking advantage of the fact that students' initial choice of high school was determined before the policy change, I analyze how the average performance of their original high school affects the likelihood of switching. Here, I use an event study design comparing students who started

[8] Low-performing schools are schools that have, on average, lower GPAs historically.

[9] The RR policy had three main implementation stages. In 2012 it was released without explaining how it worked to students. In 2014 they released information on how the RR was calculated and the comparison group they use in its formula. Finally, in 2015 they changed the comparison group to reduce students' incentives to switch high school *at the last moment*.

[10] I measure aspirations using parents' answers to the SIMCE questionnaire.

twelfth grade in a high-performing school with their peers in non-high-performing schools yearly from 2010 to 2016 with respect to 2013.[11] I find that students who started senior year in elite high schools are 8 percentage points more likely to switch in the year the information was made publicly available. Furthermore, when analyzing heterogeneities by school type, I find that the increased likelihood of switching is entirely driven by students in elite public schools.[12]

Related literature: This paper is related to several strands of the literature. First, it contributes to the understanding of unintended consequences of educational policies, especially in the pre-college stages of the human capital accumulation cycle. Previous research has shown that college admission policies affect effort (Grau, 2018; Bodoh-Creed and Hickman, 2018; Tincani et al., 2021; González and Johnson, 2018), hours spending studying (Caldwell, 2010), attendance (Akhtari et al., 2020), the probability of dropping out (Cáceres-Delpiano et al., 2018), high stake exam scores (Antonovics and Backes, 2014; Bleemer, 2020; Akhtari et al., 2020; Laajaj et al., 2022), and race-segregation levels in high school (Estevan et al., 2018). I contribute to this literature by showing how an educational policy rewarding students differently depending on the school they graduated from can create unintended reactions in students who are not the targets of said policy.

A closely connected literature studies affirmative action's impacts on school choice (Cullen et al., 2013; Mello, 2021; Estevan et al., 2018). These papers also find that students react to affirmative action policies that give direct access to college if they attend certain high schools (Texas Ten Percent Law) — Cullen et al. (2013)– and policies that provide an advantageous cutoff to attend federal universities (the case of Brazil) – Mello (2021). Relative to these papers, I show that high socioeconomic status (high-SES) students are more likely to respond strategically to the policy. I also quantify the policy's effect if students could not game the system. I can contribute in these areas because I have the information and the allocation algorithm of the centralized college admission system, and I observe students' grades and schools at the beginning and end of each academic year. This detailed novel dataset allows me to calculate the effect of switchers in the equilibrium allocations between students-majors, which Cullen et al. (2013) and Mello (2021) were unable to do with their

[11] I rank schools by types: public, charter, and private, using the average SIMCE score from the first year available, that is, 2006.

[12] These schools are highly competitive, and their students rarely switched schools before the policy change. On average, the likelihood of switching from one of these schools was about 2 percent before 2014.

dataset.

Additionally, I contribute to the literature by estimating the effects of admission policies. This literature has shown that the context and the design of policies matter when analyzing the outcomes for disadvantaged students (Andrews and Stange, 2019; Angrist et al., 2020; Harris and Mills, 2021; Kapor, 2015; Long et al., 2010), and the distributional effects of different college admission policies (Otero et al., 2021; Bleemer, 2020; Black et al., 2020; Melo, 2021; Reyes, 2022; Bucarey, 2017). I contribute by presenting evidence that the RR policy's design affected its results by creating pre-college strategic responses, which made the policy less effective. Reyes (2022) is closely related to this paper since it evaluates the same policy's effects on college enrollment, graduation, and labor outcomes for the year where there was no incentive to switch due to unshared information. I complement her analysis by focusing on pre-college responses to the policy and its effects on college acceptance rates.

My results also add to the large literature investigating which school characteristics are valued by parents and students, e.g., school quality (Epple et al., 2004), high-stake exams (Angrist et al., 2013), peer quality (Abdulkadiroğlu et al., 2020; Abdulkadiroğlu et al., 2017; Haeringer and Klijn, 2009; Rothstein, 2006; Epple et al., 2004), college attendance, earnings (Abdulkadiroğlu et al., 2020), and crime (Beuermann et al., 2022). My paper contributes to this literature by presenting evidence that original school preference can be negated by the chance to improve one's college access. In general, it is often assumed that parents would not want to send their children to poorer-performing schools if they are otherwise similar to higher-performing schools, e.g. similar in distance, price, etc. Still, my findings show that such general preferences can be changed if the benefit is high enough.

Finally, this paper adds to the literature evaluating the effects of relative grades on student outcomes (Calsamiglia and Loviglio, 2019; Elsner and Isphording, 2017; Diamond and Persson, 2016; Rangvid, 2015). In line with previous findings, I show that better-performing schools lead to lower college application scores for many high-achieving students, which in turn affects students' college admission rates, leading them to switch to lower-performing schools to obtain higher relative ranking scores.

The rest of this paper is organized as follows. Section 2 describes the institutional setting, while Section 3 discusses the data used in this paper. Next, Section 4 gives the results of the policy by school performance and students' socioeconomic backgrounds. Section 5 presents the stylized model for understanding the incentives for switching high schools and its effects in equilibrium. Section 6 describes how the potential application score gain from switching schools relates to students' characteristics. Then, Section 7 presents the empirical strategy and results for students' switching decisions. Section 8 discusses the problem of using high school to target disadvantaged students and, therefore, increase low-income students' college acceptance rate. Finally, the 9 provides the final commentary.

2 Institutional Background

Although Chile is a middle-income country with a GDP per capita close to 14,750 USD in 2019,[13] income and education inequality in the country remains high. Estimations from the World Bank for the GINI coefficient position Chile with similar results to the US (44.4 for Chile in 2017 and 41.4 in 2018 for the US). When considering access to college, results are also intriguing; in 2019, 85.2% of adults between 25 and 34 years old had at least a high school diploma, but only 33.7% had a higher education one. Moreover, Narayan et al. (2018) ranks Chile among the least mobile countries in the world, using the share of individuals in the 1980s cohort born into the bottom half and who have reached the top quartile.

Since 2003, in Chile attending four years of secondary education has been compulsory for students aged 14 to 17.[14] A key characteristic of the educational system is parents' high degree of choice: a family seeking schools for their children can choose within and between free public, private voucher, and private non-voucher schools for primary and secondary education.

Despite the high degree of options available, students from poorer families tend to go to schools with lower outcomes in terms of test scores and lower inputs in terms of teacher quality and overall resources (Alves et al., 2015). Figure 1 shows the distribution of schools' average performance, measured by the mean standardized score at the school level for students in tenth grade in 2008 and the mean standardized score at the school level for students in twelfth grade in 2010 by the students' socioeconomic status.[15] We see that low-SES students perform worse on average than students with higher SES. The mean performance does not change much for low-SES students when

[13] Source: World Bank.

[14] Chile has had mandatory schooling for primary school since 1965. Source: Congreso Nacional de Chile.

[15] I use mother's educational status as a proxy for students' socioeconomic status (see Section 3 for a discussion about it).

we compare the results in tenth and twelfth grades; however, it worsens for students with higher SES.

The connection between schools' performance, students' socioeconomic status, and opportunities to attend college has been a key motivator for policy changes in the country. In 2011, for example, Chile experienced one of the longest strikes from students demanding changes in the educational system, known as the Chilean Winter Gray.[16] Advocates of changes in the system argue that the low quality of schools translates directly into a lower probability of going to college for students coming from low-quality schools, regardless of their ability and performance during school. The RR policy that I study in this paper was designed to increase opportunities of being accepted in colleges for students performing well, taking into consideration the differences in the schools' quality they attend (see Section 2.4 for more details).

2.1 Secondary Education in Chile

The graduation rates in secondary school in Chile are high. In 2019, the dropout rate for grades nine to twelve was less than three percent.[17] However, there is an important difference in the quality of high schools students attend depending of their socioeconomic background. Figure 2 presents the relationship between schools' ranking measure in 2006 and the percentage of students with free lunch in the school in 2010. As we can see, a positive correlation exists between school ranking and the school's vulnerability index, with a correlation of 0.77.

In Chile, the academic year starts at the beginning of March each year and ends during the second week of December. However, for twelfth-grade students, the relevant timeline ends in January of the following year, with the enrollment in the matched *college-major* of their preferences. The key months during the college application process for students in twelfth grade are June, when the application information is released, September, which is the last month when students can switch high schools, December, when students take the standardized admission test; and January, when they apply to their ten most preferred *college-major* and enroll in one of them if they have matched. Figure C.1 presents the academic and college application processes timeline relevant for students graduating from high school.

[16]The current president of Chile was one of the leaders of this movement. See: The Guardian.
[17]Source MINEDUC

2.2 Tertiary Education in Chile

Universities rank applicants using an application score (AS) in the centralized admission system. The AS is a weighted sum of the national standardized test (PSU), students' grades during high school (GPA), and the relative ranking (RR).[18] Table 1 shows colleges' main characteristics, such as the average number of seats and tuition in 2014, by type of institution, and admissions system. Institutions have been generally classified as universities (public or private), Centros de Formación Tecnica (CFT), or Institutos Profesionales (IP).[19] Out of 144 post-secondary institutions in the country in 2014, 25 belong to the centralized system (16 public and 9 private).

Although tuition and other characteristics are similar among institutions (see Table 1), universities using the centralized system are better in terms of quality and perception. Among the best universities in Latin America in 2022 THE ranking,[20] Pontificia Universidad Catolica and Universidad de Chile ranked first and seventh, respectively.[21]

2.3 Application to College

All the students who desire to attend college have to: (i) finish high school with an average GPA at least equal to 4 (up to 7),[22] (ii) take the PSU[23] offered once per year in the middle/end of December, and (iii) applies to the ten most preferred college-major combinations. During the application process, students can choose whether to apply for admission in a centralized or non-centralized system. In 2014, 44 percent of the students who took the PSU applied to at least one program in the centralized system.[24]

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[18] The RR was incorporated into the system in 2012 (see section 2.4 for more details).

[19] CFT and IP are similar to community colleges in the US. They mainly offer two-year programs with the option to transfer to a private university after finishing the two years.

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

[21] All the other Chilean universities in the top 50 belong to the centralized system.

[22] The centralized system calculates the standardized GPA at high school (NEM) using the average GPA during the four years of high school. The lower bound is 200 (when a student has a 4-year average of 4.0), and the maximum is 822 points (when a student has a 4-year average of 7.0).

[23] Composed of verbal (mandatory), quantitative (mandatory), and history or science tests. Each one of these tests has normally-distributed scores with a mean of 550 points and a standard deviation equal to 110. The score is truncated on the lower and upper tails at 220 and 850 points, respectively.

[24] In this paper, I focus only on students applying at least to one university through the centralized system for several reasons: (i) the most selective institutions belong the system; (ii) students have incentives to switch schools only if they are applying to universities belonging the centralized system; and (iii) it is not possible to recover preferences for students who did not apply to the centralized system. For more details about the application process, see Barrios-Fernandez (2021), and Larroucau

To match students and programs, Chile uses a modification of the deferred acceptance (DA) algorithm. This matching process combines student preferences with degree preferences to generate a single program assignment for each student. In the initial step of the algorithm, each student proposes to their first-choice degree. Majors accept students in order of ranked AS up to capacity and wait-listed the rest. In subsequent rounds, each student wait-listed in the previous step proposes their most-preferred major among those that have not previously wait-listed them, and majors wait-list provisionally accepted applicants in favor of new applicants with higher AS. This process iterates until all students are assigned to a program, or all unassigned students have been wait-listed by every program they have ranked. In my study of the applicant pool between 2010 and 2014, twenty-three percent of the students are not accepted into any of the universities to which they applied.

An attractive theoretical property of the DA mechanism is that it is strategy-proof: since high-priority students can displace those with lower priority in later rounds of the process, listing schools in order of true preferences is a dominant strategy in the mechanism's canonical version (Abdulkadiroğlu et al., 2020; Dubins and Freedman, 1981; Roth, 1982). This property, however, requires students to have the option to rank all schools (Haeringer and Klijn, 2009; Pathak and Sönmez, 2013). Table 2 reports the fraction of students listed in their application from one to ten choices (column 1) and which fraction of admitted students were accepted in a particular choice (column 2). Column 1 shows more than ninety percent of students rank fewer than 10 majors, meaning that truthful ranking of schools is a dominant strategy for the majority of applicants, and about one-half submit 5 preferences. Column 2 shows that about seventy-five percent of the students admitted are admitted in one of their three most preferred majors. In the analysis to follow, I interpret students' rank-ordered list as truthful reports of their preferences (Abdulkadiroğlu et al., 2017).

Finally, to help families in their decision-making process, the organism in charge of the application (DEMRE) has a website that provides an overview of the college admission process, key dates, and information about each university that uses the centralized admission system.[25]

and Rios (2020).

[25]See https://demre.cl/index for more website's details.

2.4 The Relative Ranking (RR) Policy

In June of 2012, as a way to help students with high GPAs but not great results on the PSU, the Consejo de Rectores de Chile (CRUNCH) decided to incorporate a new requirement to those previously detailed: the *relative ranking (RR)*. This new criterion compares students with the three previous cohorts in the high school from which they graduated. Note that since students are compared with previous cohorts in the same high school, they do not *'compete'* with students graduating in the same year for a higher relative ranking.

The standardized relative ranking is computed using a nonlinear function of the student's high school GPA: if the student's 4-year GPA were below the mean of the three previous cohorts, she would receive the same score as the NEM. If she was above this mean but below the best student among the three previous cohorts, she would receive a score higher than the NEM score for this component. Finally, if the student had a 4-year GPA higher than the best student among the three previous cohorts, she would receive the maximum points allowed for this component, which is 850 points.

Figure 3 graphically illustrates how the relative ranking is computed. The blue line represents the function mapping the student's 4-year high school GPA to her SGPA score; meanwhile, the red line illustrates the nonlinear function between average GPA and standardized relative ranking. $\underline{r}_S$ represents the average GPA across three previous cohorts, and $\overline{r}_S$ represents the maximum GPA in three previous cohorts.

To understand why students may have incentives to switch high schools, it is relevant to understand the policy chronologically. First, between the 2012 and 2013 academic years[26] students were not informed how the relative ranking was computed. Second, all the belonging and adjunct universities to the Chilean Council of University Rectors (*Consejo de Rectores de las Universidades Chilenas* - CRUNCH) adopted a 10 percent weight for the relative ranking in the process in 2012, only altering the GPA weight. However, in 2013 they modified the weights for all three requirements. Third, in 2014 CRUNCH made transparent and public how the relative ranking was computed. This revelation made it known that in 2012-2014 the relative ranking only compared each student with past cohorts from the high school she was at when she applied to college rather than all schools she potentially attended in the 4-year high school process. Finally, in 2015 the CRUNCH changed the policy so that the comparison group for each student is composed of all of the schools she attended

[26]Application process to start college in 2013 and 2014 academic year respectively.

throughout high school (see figure 4 and appendix A for more details).

Figure 5 presents the ranking component for two schools with different thresholds. We graphically see that some students in school S with the same GPA would have a higher relative ranking if they graduated from school E because the thresholds are lower. This represents an increase in students' application scores derived only from graduating from one school or another.

3 Data

This paper combines several sources of data from the Chilean educational system covering all students enrolled in twelfth grade in the country between 2010 and 2016. The final dataset includes school enrollment, student demographics, scores on tenth-grade standardized tests, PSU scores, primary and high school annual GPA, along with preferences submitted to the centralized college assignment mechanism. Supplemental information reports high school characteristics and college enrollment for students attending colleges using the centralized system.

To create the final dataset, I combine the Department of Education's publicly available data containing students and high schools characteristics with records from the college admission system from the *Departamento de Evaluación, Medición y Registro Educacional* (DEMRE).[27] I complement the data described above with three other sources: (i) administrative data from the Education Quality Measurement System (SIMCE), (ii) detailed high school information, e.g., geolocation, type of school (private, voucher or public), number of teachers, etc., and (iii) information of each college-major, e.g., weights, number of seats, program characteristics, for institutions belonging the *Consejo de Rectores de Universidades Chilenas*.

I use three different *main* dataset in this paper. First, I use a dataset to evaluate the policy effects, which contains students applying to college in 2014, the weights, and other universities' characteristics from 2014, and 2010.[28] Second, I use data that allows me to analyze who has incentives to switch, containing students graduating from high school at the end of 2012, 2013 and 2014, primary schools and high school geolocation, and thresholds used for the RR calculation. Finally, the third dataset characterizes students who behave strategically to gain the policy by

[27]It contains information on the national test scores (PSU), ranked application (up to 10) of college/major, and household characteristics for each student-preference level.

[28]Students and anyone can access this information in https://demre.cl/psu/publicaciones/listado-2016.

switching schools. This dataset contains students' initial and final schools in grade twelfth between the years 2010 to 2014, school characteristics, such as ranking, number of teachers, total enrollment and school type (public, charter, private), students characteristics, e.g., gender, age, municipality of residency.

I merge this dataset with tenth-grade standardized test scores and surveys to incorporate more students' characteristics, especially regarding their socioeconomic background. Additionally, I combine the dataset with students taking the standardized national test at the end of high school. Although the test happens after they make the switching decision, we would expect that some self-reported characteristics, like the mother's education, would be invariant in the less-than-one-year interval of time.

3.1 Data limitations

There are three limitations to my dataset. First, I do not observe students' socioeconomic status. Currently, available records present self-reported information for income in brackets only. This information is used in the college admission process to access scholarships and loans; therefore, one could be concerned that there is a measurement error biasing the observed income variable in my dataset. Specifically, we could expect that this variable is under-reported by students since they get financial aid depending on this variable. To overcome this problem, I use students' mother education as a proxy. There are at least two advantages of using this variable instead of income. First, financial aid is not tied to the mother's educational outcome. Second, I combine the self-reported mother education variable at the end of grade twelfth with a survey that parents answered in grade tenth. I lack information to check the correlation between students' SES and their mother's education, but I can use the vulnerability index at the high school level to calculate how the two variables interact. Figure 6 presents the correlation between mothers' education and schools' vulnerability index in 2010. The raw correlation between the percentage of students whose mothers do not have a high school diploma and the vulnerability index at the school level is 0.8272.

The second issue is the lack of student addresses that I use to determine the relevant market for each student. To overcome this issue, I use the student's primary school locations as a proxy of students' addresses and estimate buffers of 2, 4, 6, and 8 kilometers using the primary school as the center.[29] Figure C.2 presents the real

[29] The idea behind this proxy is based on the connection between distance to school and families'

distance between students' primary and high school in 2014. Over sixty percent of the students in grade twelfth choose a high school closer than 5 kilometers from their primary school.

Finally, I do not have the exact algorithm used to allocate students into listed majors. I use the DAA algorithm developed by professor Sergey Lychagin[30] as default and calculate allocations for each possible scenario. Using the 2014 pool of applicants and their real application scores (reported in the administrative records), I test the algorithm. I recover 100% of the real students-degree allocations for that year.

4 Effect of the policy in colleges acceptance rate

In this section, I look at the effect of the policy on students applying to college in 2014. Recall the policy aims to increase the representation in college of students from lower-ranked schools and students from lower socio-economic status. Overall, I find that the policy has a small effect on increasing low-SES students' acceptance ratio, with differential effects depending on how selective colleges are. When considering school performance, the policy had a smaller effect than it could have if students did not switch schools, reducing the effect to 2/3 of the expected results.

4.1 Descriptive statistics

Table 3 presents the main characteristics of cohorts graduating between the years 2009 and 2010. The first column shows the mean and standard deviation of several students' and high schools' characteristics. Overall, 75% of the students have mothers with at least a high school diploma, and 32% of the sample of students live in the metropolitan area of Santiago.[31] Most of the students attend public or voucher schools, 33%, and 53%, respectively. When considering school quality, measured using tenth-grade standardized test scores taken in 2006, 52% of the students applying to college are in high-quality schools.[32]

school choice found in the school choice literature focused on primary schools (Neilson, 2013; Allende, 2019).

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

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

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

Each of the rows in columns (2) to (4) reports the OLS coefficient and standard errors, in parentheses, of a regression of students' characteristics on a dummy variable equal to 1 if the student was accepted in college (column 2), accepted into one of the two most selective colleges (column 3) or accepted into the other 8 more selective Chilean universities (column 4), clustering standard errors at the municipality level.[33] In general, students considered high achievers with mothers who have at least a high school diploma are more likely to get accepted in college, with more pronounced differences in the rate of acceptance for the top two colleges in the country. Interestingly, although students in metropolitan region are less likely to get accepted in any college, they are 33% more likely to be accepted in the top colleges. Students from public and charter schools are less likely to get acceptance in top colleges, and students from high quality schools are more likely to get any acceptance. These statistics are consistent with the government's priors to the RR policy, and the main reason why they incorporated it; students from less privilege backgrounds are less likely to get accepted in college.[34]

4.2 Policy effects by student's SES and school's quality

I compute the effect of the policy in the pool of accepted students in college using simulations over the same pool of applicants. I use this methodology for two reasons. First, the policy timeline makes harder to use any type of difference-in-difference design controlling for trends (see Figure 4). Second, I am interested in the total distributional effects of the policy, so any design, such regression discontinuity will only capture the effect on the marginal student.

To calculate the allocation of students into college without the policy, I leverage the formula used to calculate students' application score in 2011 and compute, for students applying to college in 2014, what would be their score with this old formula. I also calculate students application score with and without relocation. I do this for the real score (the one students have after the switching school decisions) to reduce concerns about measurement error. Similarly, I use majors' available slots in 2014, to eliminate allocation changes due to increases/reductions in the slots available between different years, Figure C.5 in appendix C presents the average number of slots in the system between years 2010 to 2014.

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

[34] https://www.cooperativa.cl/noticias/pais/educacion/psu/cruch-defendio-el-ranking-de-notas-contribuye-a-la-equidad/2013-09-12/182443.html.

I present results for students by school and SES in Figures 8, 9, and C.3 considering overall rate of acceptance, acceptance rate in tier 1 and tier 2 colleges. Figure 8.a presents the results by initial school quality. In the first exercises (four first columns), I calculate the effect of the policy if students graduated from the school they started the year (*benchmark effect*). In this case, I find that the policy would increase the number of accepted students from low quality schools, in the centralized system, by 3 percents. I find a similar results when student switches schools (*real effect*), showed in the next four columns. I argue this is expected since the rate of acceptance conditional on applying to *any* college is about 80% in 2014 (see Figure C.6).

Results are different when analyzing most selective schools (see Figure 8.b). In this case, the policy effectiveness is reduced by 1/3 of the results it would have if students did not switch schools. Here the effect of the movers decrease the effect of the policy in more than 3 percentage points (last four columns).

For student's SES, we see a lower increase in the acceptance rate for low SES. I find that the policy increased the acceptance rate for students from low background around 1.5 percent in *any* university. The ex-ante expected increase for top colleges was around 4.5 percent. In this case, movers undermined the policy effectivenes almost entirely (see Figure 9).

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

5 Conceptual Framework

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

In the first part of this section, I build theoretically students' potential gain due to the policy. Next, I present a model for switching decision that incorporates cost of switching. I end this section analyzing how the application cutoff and college body composition change in different scenarios.

5.1 Potential gain in students' application scores

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

I consider a setup where students have already been assigned to one high school, and their only decision is whether or not to switch to a new high school. Although the earlier school choice decision is important, and has been analyzed extensively before (Alves et al., 2015; Pop-Eleches and Urquiola, 2013; Hastings et al., 2012; Neilson, 2013; Allende, 2019), I consider the school where they start as given and focus on the switching decision only. College C is characterized by its capacity constraint K and its preferences over students application scores. For the purpose of the model, I assume here students score depends only in the relative ranking.[35,36] Students are characterized by their GPA: $gpa_i \in (\underline{g}, \overline{g})$, and their started high school, $s \in \{L, H\}$.

Before the policy, student i's application score (AS_i) is a function of their GPA only:[37,38]

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

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

[35] Although in Chile the application scores are determined using weights to each requirement (PSU, high school GPA and ranking).

[36] This assumption is possible if average GPA at high school and PSU scores do not change with the switching decision.

[37] This formula comes from the system. See MINEDUC.

[38] Notice the AS is the same no matter the school student i's graduated from.

graduated from -school e-:

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

This non-linear function implies: (i) student gets the same AS than before the policy if they are not above graduation school's mean threshold, (ii) student obtains a school-specific bonus if they are above the mean threshold but below the maximum threshold in the school, and (iii) student obtains the maximum points possible whenever they have a GPA higher than the best student in the three previous cohort -maximum threshold-.

Figures 10 and 11 graphically present the cases for all the possible combinations of threshold between two schools. I assume a student starting twelfth grade in school s has a potential gain in the application score by switching to school e if:

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

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

In Figure 10 students from school, s have a potential score gain by switching to school e, but no one from school e is better off, in AS sense, switching to school s, I call this case *downward switching*. On the other hand, we can see in Figure 11 that whenever the dispersion within school e's thresholds is lower than in school s, some students in both schools could benefit from switching schools.

5.2 A simple model of switching schools

The model developed in this section builds on Cullen et al. (2013) and Estevan et al. (2018) theoretical models. Assume all students are applying to college[39], and derive a utility U_{iC} if they are accepted into it. If they are not accepted, their utility is 0.

All the students are ranked depending of their application score when applying to college. The college allocation mechanisms is such that students with an applications score higher than the cutoff are accepted into college,[40] where the cutoff is an

[39] Although this is a strong assumption, due to the fact that the policy changes the application scores that might create incentives for some students to switch schools, it is reasonable to only analyze the pool of students interested in the application process.

[40] If K¡1 only fraction of the total population, normalized to one, is accepted into college.

equilibrium outcome.[41]

I assume students pay a cost, $c_{ise} > 0$ of switching from school s to school e for all $e \in \{H, L\} - \{s\}$. Additionally, students value each school differently, with $b_{is} > b_{ie}$.[42]

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

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

while their conditional utility if they switch to school e is

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

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

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

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

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

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

[41]Note that other students' decision only affect student i through changes in the equilibrium cutoff to get accepted.

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

5.3 Application score and equilibrium pool of accepted students

To characterize the equilibrium cutoff, AS^*, I need an assumption about how GPAs are distributed among students. Following Estevan et al. (2018) I assume students' GPA in schools H and L before any switching follow distributions $F_H(gpa)$ and $F_L(gpa)$ respectively, such that the aggregate distribution is given by:

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

where μ_H and μ_L are the fraction of students in each school before switching happens.[43] Given equations (1) and (8), I can then define the distributions for AS in each school, which would be a transformation of the GPA distributions. Let $G_L(AS)$ and $G_H(AS)$ be the distributions for schools L and H respectively. Under this environment, two constraints characterize the application score in equilibrium and the pool of students accepted in college under any policy τ.

Constraint 1. *Unique application score*
Due to the centralized application system, the application score in equilibrium is the same for each school. Let gpa^*_L and gpa^*_H be the student's GPA that obtains an application score equal to the cutoff in equilibrium. Therefore:[44]

$$AS_L(gpa^*_L) = AS_H(gpa^*_H) = AS^*. \tag{6}$$

Constraint 2. *College Capacity*
Let d_H be equal to 1 if $AS_H(x) > AS_L(x)$ for a GPA of x. For any policy τ not changing the capacity constraint in college, the fraction of accepted students in equilibrium must be equal to the number of seats available. Thus:

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

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

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

5.3.1 Equilibrium

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

1. $q = (q_L, q_H)$ is the vector of student accepted in college from each school, which correspond to students for whom their applications score is higher than the cutoff in equilibrium.

2. AS^* is the unique *competitive market* application cutoff given the slots available in college, subject to students acceptance rates from school L and H, q_L and q_H, which are also function of the cutoff.

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

Recall before the policy the AS function was not affected by students' schools, and only by their GPA, which I assume is determined when they take the decision of switching or not schools. To see the intuition behind this proposition use constraints 1 and 2. By Constraint 1 we know $AS_L(gpa_L^*) = AS_H(gpa_H^*) = AS^*$. Using the deterministic function between GPA and AS before the policy in equation 1, we find that $gpa_L^* = gpa_H^*$. Finally, under the assumption that both distributions are equal, using Constraint 2 and the fact that students are not moving: $G_L(AS^*) = G_H(AS^*) = G(AS^*)$. For the formal proof, see Appendix A.

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

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

and

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

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

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

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

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

For simplicity, assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L < \overline{r}_H$ as in Figure 10. Then using Constraint 1 and the fact that Equation 8 gives always a weakly higher application threshold for students in school L, $AS(gpa_i, L) \geq AS(gpa_i, H)$ for any given GPA, we have $gpa_L^* < gpa_H^*$. Now, using capacity constraint, we have:

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

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

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

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

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

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

Proposition 3 follows a similar intuition than Proposition 2. The main difference is that now, due to the switchers, the application score goes up more, whenever the cost of switching, $\tilde{c}_{ijk}$, is strictly lower than the value of college (see proof in Appendix A). To see why the change in the pool of accepted students, one of the policy goals, depends on the cost of switching, suppose that cost is zero. Then, all the students who have a potential gain due to switching move. If we take the case shown in Figure 10, we have that students with a GPA between $gpa^*_L = AS^{-1}_L(AS^*_2)$, and $gpa^*_H = AS^{-1}_H(AS^*_2)$ switch schools. If this is the case, then the effect of policy on the number of students accepted in college from school L is reversed, and there is no change in the pool of students accepted into college.

Corollary 1. *Let AS^*_0 be the application score in equilibrium before the policy, AS^*_1 the application score in equilibrium when the policy is implemented and students are not allowed to switch, and AS^*_2 the resulted score after students relocate schools. Then*

$$AS^*_0 \leq AS^*_1 \leq AS^*_2.$$

5.4 Model's main predictions

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

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

6 Students' potential gain

In this section, I present the empirical analysis of students' potential score gain and characteristics that correlated with it. The goal is to understand who the students with high *potential score gain* are and how this variable correlates with students' and schools' characteristics.

I define *potential gain* as the highest gain in application score for each student. Therefore, I calculate the application score they would have if they switched to any other school in their choice set and compare it with the score they had graduating from the same school they started twelfth grade. One key part for this calculation is to recover students relevant choice set for the switching decision. For this, I follow previous literature (Neilson, 2013; Allende, 2019), and compute buffers of 2 to 8 kilometers center in student's primary school.[45] In the case that high school they graduated from is not in the calculated buffer, I incorporate it to be part of it.

For this exercise to be informative about students switching schools as a result of the gain created by the RR policy and its effects in college acceptance, two assumptions must hold. First, other components of the college application score, i.e. PSU and NEM, should not be affected with students' relocation of schools. Second, students' preference over degrees they apply to should not change with the policy.

For the first assumption, there are two facts that reduce the concern. First, I focus on students who switch in graded twelfth, while the NEM and PSU considers grades and knowledge, respectively, obtain during all high school (grades 9 to 12). Further, Figure 12 presents the number of student switching schools in twelfth grade from 2011 to 2015, depending on when they switch,[46] for all students (panel a) and for students in a top schools in the country (panel b). The trend suggests students spend less than a year in the new school, since the increase is mostly derive by movers during the year, reducing the concern of potential changes in PSU score and NEM after switching schools. For the second assumption I leverage the college admission system allocation mechanism, since it creates incentives for students to truly reveal preferences (see Subsection 2.3).

[45]See subsection 3.1 for details on data limitations.

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

6.1 Descriptive statistics

In this subsection I present descriptive statistics for the sample used to calculate students' potential gain due to the RR policy. Figure 7 shows the percent of students with positive potential gain for years 2012, 2013 and 2014. In the three-year interval, approximately seventy percent of the students in grade twelfth would have a positive gain by switching school within their choice set. For 2014, I recover primary school and connect high and primary schools geolocation for more than 90% of the students.

Table 4 presents descriptive statistics for the analytical sample measured in 2014. The average potential gain is approximately 60 points. As expected, high-achieving students have higher potential gain as students in metropolitan region also have. Private schools tend to have higher potential gain (almost 60 points), while elite schools (measured by school quality) have a potential gain of 30 points higher than the average.

6.2 Results

Recall a key component in my calculation is the students' choice set. My primary analysis uses a 4-kilometer buffer. Figure 13 summarizes the distribution of *potential score gain* and its empirical cumulative distribution in 2014. Conditional of having a gain greater than one point, 1/3 of students have less than a 30-point potential score gain (*low-gain*) another 1/3 of students has a potential score gain higher than 90 points (*high-gain*). As a sensitivity analysis of the *potential score gain* calculation Figure C.4 panel (a) presents the distribution for 2- to 8-kilometer buffer using student's primary school as the center, while panel (b) presents the same graph but using student' initial high school as the center.

As the model predicts, even if switching schools is costless and students value going to college more than the overall cost of graduating from a new school, not all the students have incentives to relocate; only students in the middle of the GPA distribution would have a positive score by switching schools. Figure 14 presents the potential gain by student's GPA. The intuition of this predictions is pretty straight forward, if a student's GPA is too low, then there is no school in their relevant market where they could be above the mean threshold. On the other hand, if a student's GPA is really high, and given that the application score is bounded from the right, they receive the maximum points possible in the system in their initial school.

Lastly, I analyze how students and schools characteristics correlates with their potential gain. Here the goal is, within score gain categories, understand what student's underlying characteristics are associated with a higher potential score gain. Table 5 presents the results of OLS regressions between potential score gain and different characteristics, the results are presented by type of gain, with the first column presenting the overall results for comparison. This results were analyzed in Table 13. There is some small significant difference (less than 2 points) for any student's characteristic within categories, but living in the metropolitan area of Santiago for high gain; in this case the difference respect to people leaving in other parts of the country is more than 20 points. For school characteristics we see similar patterns: small difference withing potential score gain group.

In essence, when analyzing the calculated application score gain for students applying in 2014 to college, there is about 70% of students who could increase their application score by switching schools in their choice set. The gain they would have varies considerably by students' characteristics, being 20 points higher than the average, for high quality schools and high SES students. This difference are substantially smaller when we consider different potential score gain levels (high, medium and low gain). Within group, there is no big systematic difference across students' and schools' characteristics and their potential score gain.

7 Students' switching decision

In this section I study which students and schools characteristics correlate with a higher likelihood of switching school in 2014. I do this analysis to evaluate if people gaming the policy are systematically different to people who did not switch, and better understand why the policy has the small results we observe.

I start by answering whether students are switching to have a better AS. If this is true, we should observe in the data a positive correlation between potential gain and probability of switching school in twelfth grade; same apply for the correlation between potential gain and realized gain when I consider only students who switch schools. Figure 15 present the correlation between these variables for 2014 and previous years.[47] The probability of switching schools for students with high gain (higher than 90 points) increases significantly in 2014 with respect to previous years, where the relation is negative between probability of switching and potential score gain (see Figure 15.a). When analysing the correlation between potential gain and realized

[47] Given that the thresholds to determine the score gain are giving for a particular cohort, I can compute the application score gain for any given cohort.

gain we observe that this variables are positively correlated in any period, but the correlation is higher in 2014 (0.10 and 0.33 respectively).

7.1 Descriptive statics

Table 6 present descriptive statistics for students in twelfth grade between 2010 and 2013 (baseline). On average, 42% of students are in public high schools and 49% percent in voucher schools. In this period, on average 3.5% of students switch schools, this mean is slightly higher (lower) for students from high (lower) SES. When considering different characteristics of students and school, we observe that high achievers are less likely to switch schools, while students in voucher schools are about half of a percentage point more likely to switch schools. Finally, students in high quality schools are less likely to move on average.

7.2 Changes across years in the likelihood of switching schools

Here I evaluate whether there is a change in the probability of switching the year of the policy for students who has a high potential gain.

To carry the analysis, I use a difference-in-difference design, here I exploit two variations within school: (i) students characteristics (e.g. parent's aspirations, access to internet, SES, starting school type and quality) and (ii) temporal (before and after the policy). The main assumptions to interpret the estimated coefficients as causal effects are the absence of previous trends in the outcome variable by groups compared in the regression, and the stability of the treatment variable (the characteristic, in my case).

The equation to be estimated is as follow:

$$y_{is(i)t} = \delta_{s(i)} + \sum_{k \in K} \alpha_k \cdot characteristic_i^k \cdot after_t + \sum_{k \in K} \gamma_k \cdot characteristic_i^k + \theta \cdot after_t + \varepsilon_{is(i)t}, \tag{9}$$

where $y_{is(i)t}$ is a binary outcome equal to 1 if student i in twelfth grade switched from school s to another school in period t. $\delta_{s(i)}$ is a fixed effect at the initial school level.

The parameters of interest are $\sum_{k \in K} \alpha_k$ that represent the change in the probability of switching school after 2014 for students in the *characteristic* groups respect to students who do not belong in this category. The most important parameters among them are students' SES, parents' aspirations, and school's quality and type. Table 7 presents the results for the estimation of equation (9) comparing 2012 with 2014 (column 1) and 2013 and 2014 (column 2).[48]

Comparing 2014 with previous years several interesting patterns emerge: within schools, students with parents who hope they attend college increase the probability of switching schools after the policy respect students whose parents do not expect them to go to college in about one percentage points, on average. Similarly, students from medium and high SES are more likely to relocate schools after the policy respect to students from low SES. Interestingly, students in high quality schools are more likely to switch schools after 2014 in 1.5 percentage points respect to low quality schools (Q1). Finally, students from public schools are almost 6 percentage points more likely to relocate schools after 2014 respect to students from private schools.

7.3 Changes in the likelihood of switching schools for students in high-performing schools

In this section, I take advantage of the fact that students chose the initial school before the policy for the analysis.

To estimate the effect of the policy on the probability of switching schools, I use an event study (ES) methodology. As usual in ES, the first difference considers general changes before and after the policy. Meanwhile, the second difference allows for different trends among a predetermined variable, in my case, the quality of the schools students started twelfth grade.[49] The identifying assumption for this design is that in the absence of the policy, the differential in the probability of switching schools between elite and non-elite schools would have evolved similarly.

The main regression to estimate is:

$$y_{is(i)t} = elite_{s(i)} \cdot \sum_{\substack{\tau=2010 \\ \tau\neq 2013}}^{2016} \beta_\tau 1\{t = \tau\} + \delta_{s(i)} + \delta_t + \varepsilon_{is(i)t}, \tag{10}$$

where $y_{is(i)t}$ is equal to 1 if student i in cohort t who started twelfth grade at school s moved to a different school during the most recent academic year. $elite_{s(i)}$ is equal

[48] I present both comparison since parents' aspirations are not available for the 2013 cohort. The results have similar patters for any of the cases.

[49] I define two types of school quality: elite and non-elite schools.

to 1 if starting school belongs to the top 25% of schools in terms of quality, and it is 0 otherwise.

To analyze whether students target ending school, I estimate equation (10) with two other outcomes: (i) a dummy variable equal to 1 if student switched to a high school with a lower average GPA and (ii) a dummy variable equal to 1 if student switched to a high school with lower number of students going to college.

Figures 16 and 17 presents results of the estimation for the unconditional probability of switching, the probability of switching to a lower mean threshold school, and the probability of switching to a school sending fewer students to college. On average, the likelihood of switching schools from an elite school increases by 15 percentage points with respect to non-elite schools in 2014. We observe a similar increase in the likelihood that students from elite schools switch to schools that send less students to college and have lower average GPA's.

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

8 Discussion

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

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

In this paper, I show that school switching is an important unintended consequence that undermines the goal of this policy. Using students' graduation school as the treatment when evaluating the policy might *help* to inflate the effects of the policy. Figure 18 shows the effect of the RR policy considering the twelfth-grade starting school (first columns) and the graduated from school. The effect of this policy is clearly misleading (and overestimated) if we consider measuring it by the graduating school.

9 Conclusion

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

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

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

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Tables

Table 1. **College main characteristics by allocation system and type of institution (2013).**

	Centralized Admission		**Decentralized Admission**		
	Public Univ.	Private U - Crunch	Private U not-Crunch	IP	CFT
	(1)	(2)	(3)	(4)	(5)
Panel 1: *College characteristics*					
Slots	38.00	46.17	43.93	43.95	47.98
Annual tuition (in CLP)	2,198,568.67	2,442,093.45	2,366,950.65	1,238,496.01	1,185,249.22
Ratio stem degree	0.39	0.45	0.33	0.26	0.02
Ratio accredited majors	0.37	0.40	0.32	0.24	0.21
Number of institutions	16	9	34	41	50
Number of programs	853	549	2033	3188	1630
Panel 2: *Enrolled students*					
Total enrollment	39,419.00	29,767.00	76,491.00	126,624.00	65,428.00
Total female enrollment	19,229.00	13,886.00	42,021.00	62,445.00	32,972.00
Panel 3: *Application requirements' weights*					
average weight high school GPA	15.82	17.90	22.75	70.00	80.00
average weight relative ranking	26.04	22.60	16.86	.	.
average weight PSU verbal	20.67	18.07	38.04	24.67	.
average weight PSU quantitative	24.64	28.60	40.89	25.33	.

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

Table 2. **Preferences rankings in the submitted lists (2013).**

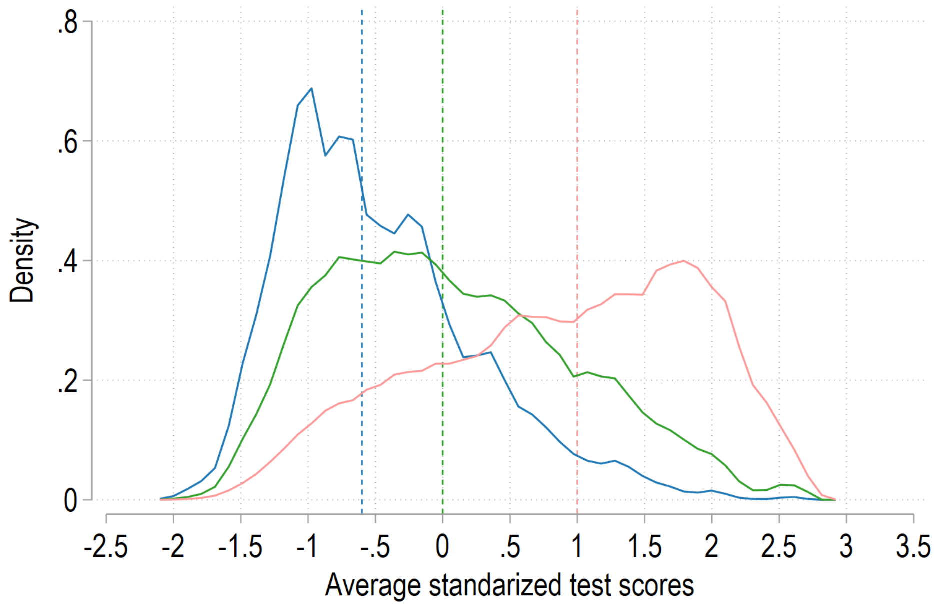
	Fraction reporting	Fraction admitted
	(1)	(2)
Choice 1	1.000	0.444
Choice 2	0.926	0.194
Choice 3	0.813	0.117
Choice 4	0.592	0.069
Choice 5	0.418	0.050
Choice 6	0.285	0.039
Choice 7	0.197	0.029
Choice 8	0.137	0.021
Choice 9	0.092	0.013
Choice 10	0.064	0.013
Nb. students	119,161	95,568

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

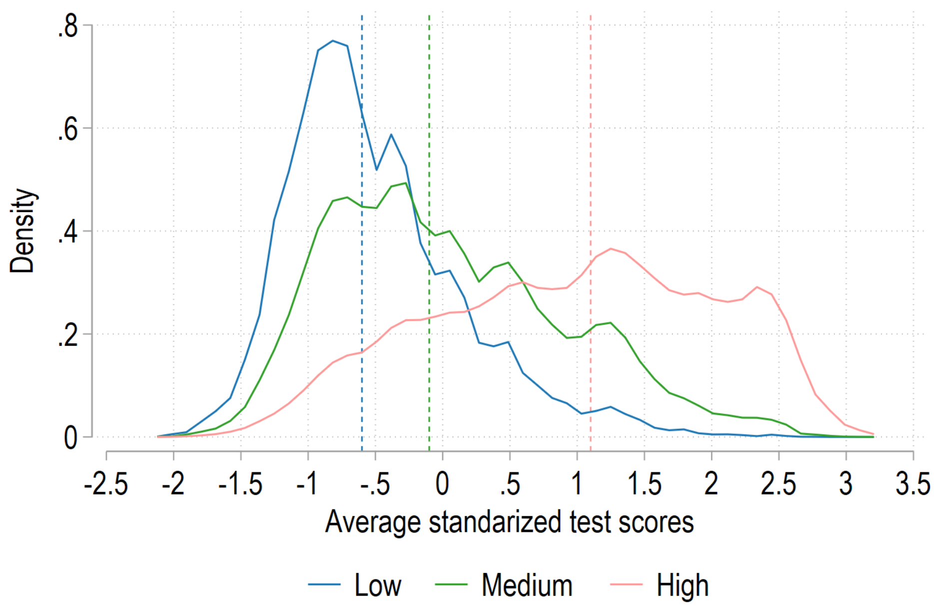
Figures

Figure 1. **School average performance across socioeconomic status (SES)**

(a) Distribution performance in tenth grade

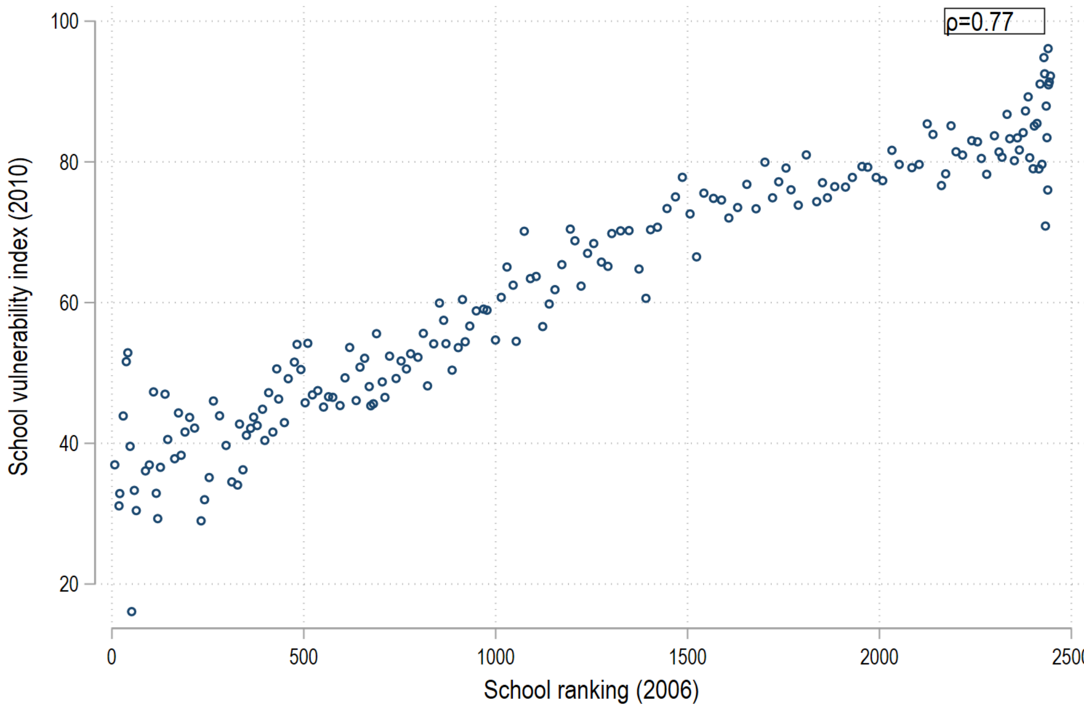


(b) Distribution performance in twelfth grade



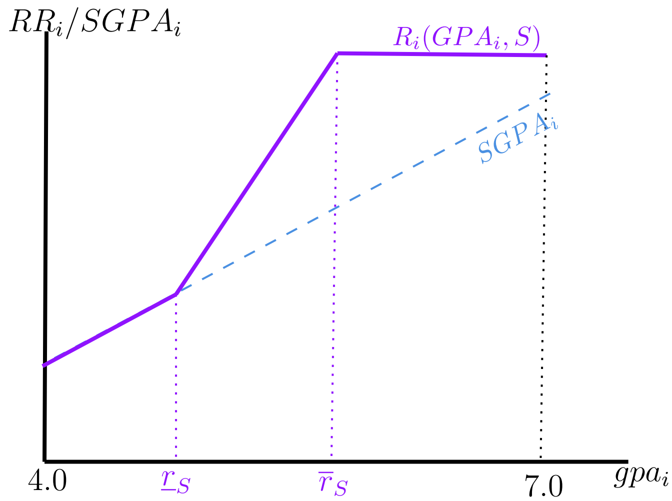
Notes: This figure depicts a histogram with mean quantitative test scores for students in tenth grade in 2008 and at the end of high school by mothers' education. Light blue represents students with mothers with less than a high school level of education. Dark purple shows the distribution for students with mothers with a high school diploma. Green plots the distribution for students with mothers who have at least incomplete tertiary education. Vertical lines represent the mean for each group.

Figure 2. **School vulnerability & school ranking**



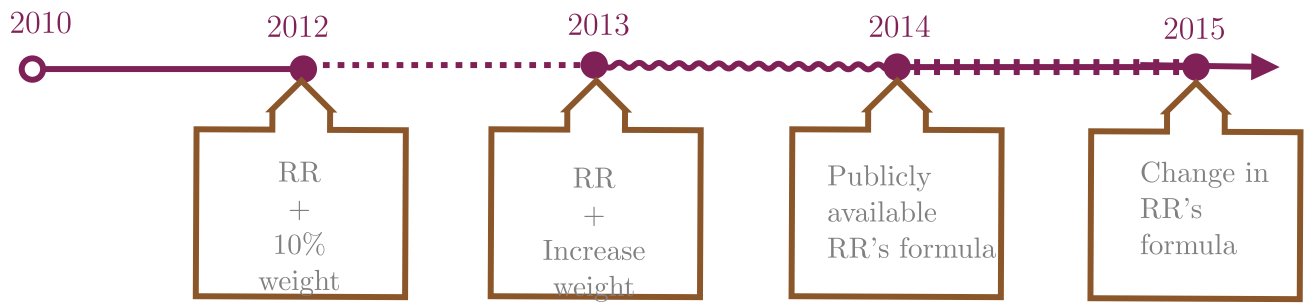
Notes: This figure presents the associations between school ranking (x-axis) measured using standardized school tests in grade 10 in 2006 and school vulnerability index (IVM) measured as the percentage of students getting free lunch (y-axis) in 2010.

Figure 3. Relative ranking component visualization



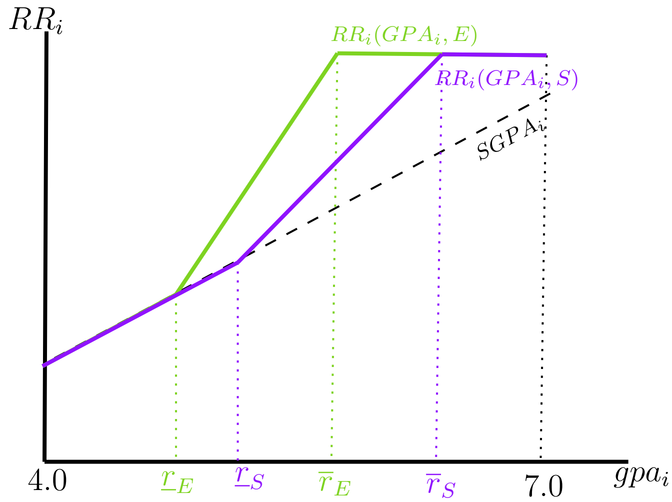
Notes: This graph depicts the formula used in Chile to create the relative ranking (RR). The blue dashed line shows the formula for student's standardized GPA (NEM) as a function of student's GPA. The purple solid line represent the non-linear formula to calculate the RR as a function of the GPA. $\underline{r}_S$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

Figure 4. Relative ranking policy's timeline



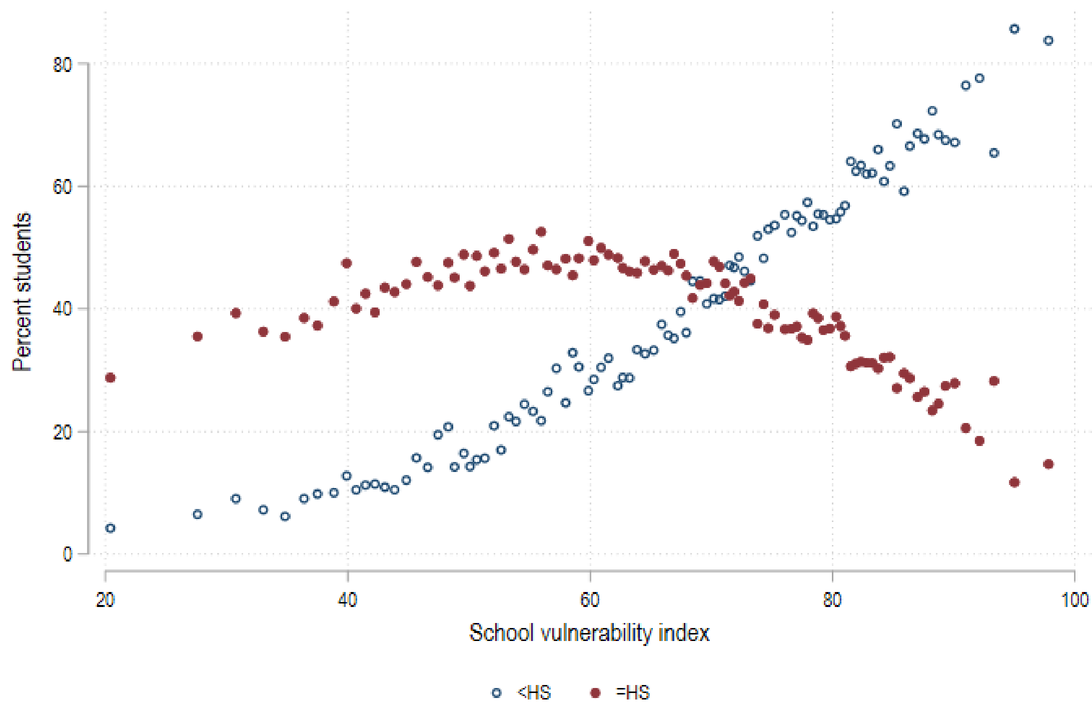
Notes: This timeline presents the changes made to the RR policy in different years. In 2012 they incorporated the policy with a weight of ten percent. This weight was subtracted from NEM's weight. In 2013 universities increased the weight associated to the RR. This new increase was coming either from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

Figure 5. Relative ranking for two schools with different thresholds



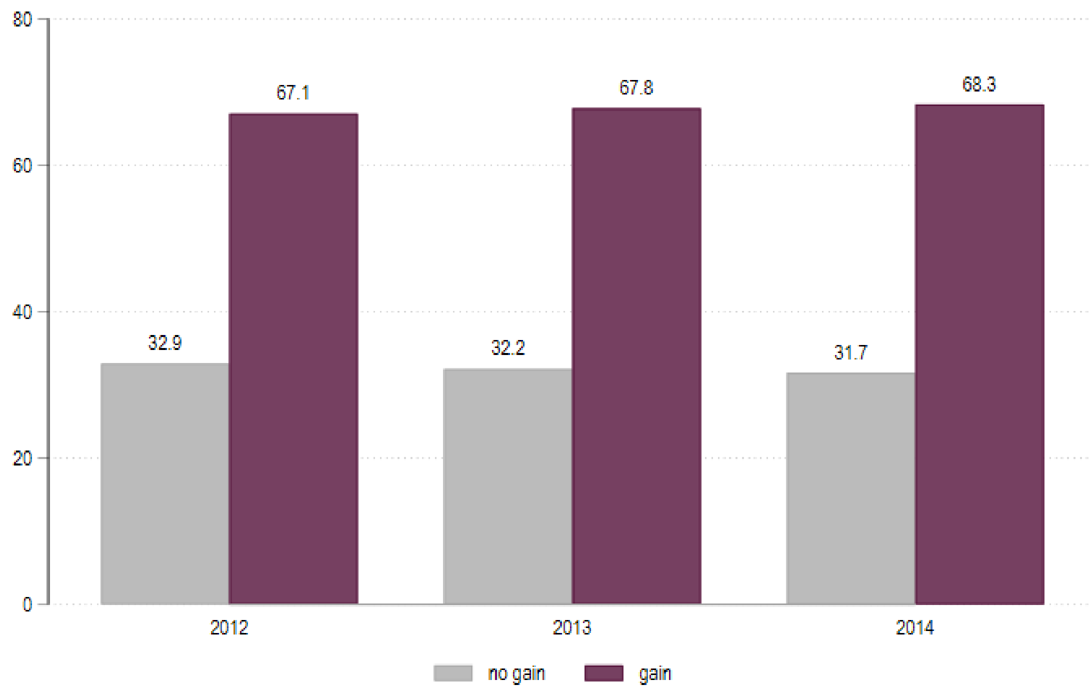
Notes: This graph depicts the formula used in Chile to create the relative ranking (RR) for two schools with different thresholds. The dark dashed line shows the formula for student's standardized GPA (NEM) as a function of student's GPA. The purple solid line represent the non-linear formula to calculate the RR as a function of student's GPA in school S. The green solid line represent the non-linear formula to calculate the RR as a function of student's GPA in school E. $\underline{r}_S$ and $\underline{r}_E$ represent the mean of the three previous cohort who graduated in school S and E, respectively. $\overline{r}_S$ and $\overline{r}_E$ represent the maximum threshold in school S and E.

Figure 6. Students SES and school vulnerability (2010).



Notes: This figure presents the average percent of students with mother's education lower than high school ($< HS$) and mother's education equal to high school diploma ($= HS$) by school 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.

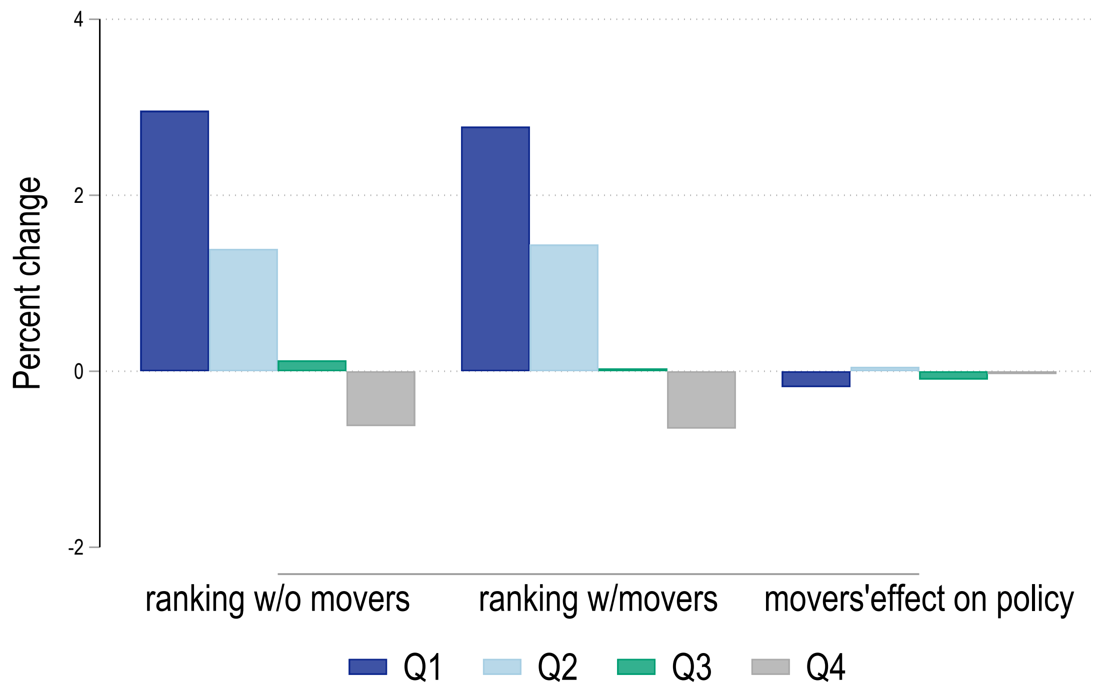
Figure 7. Ratio students with positive potential gain (2012-2014).



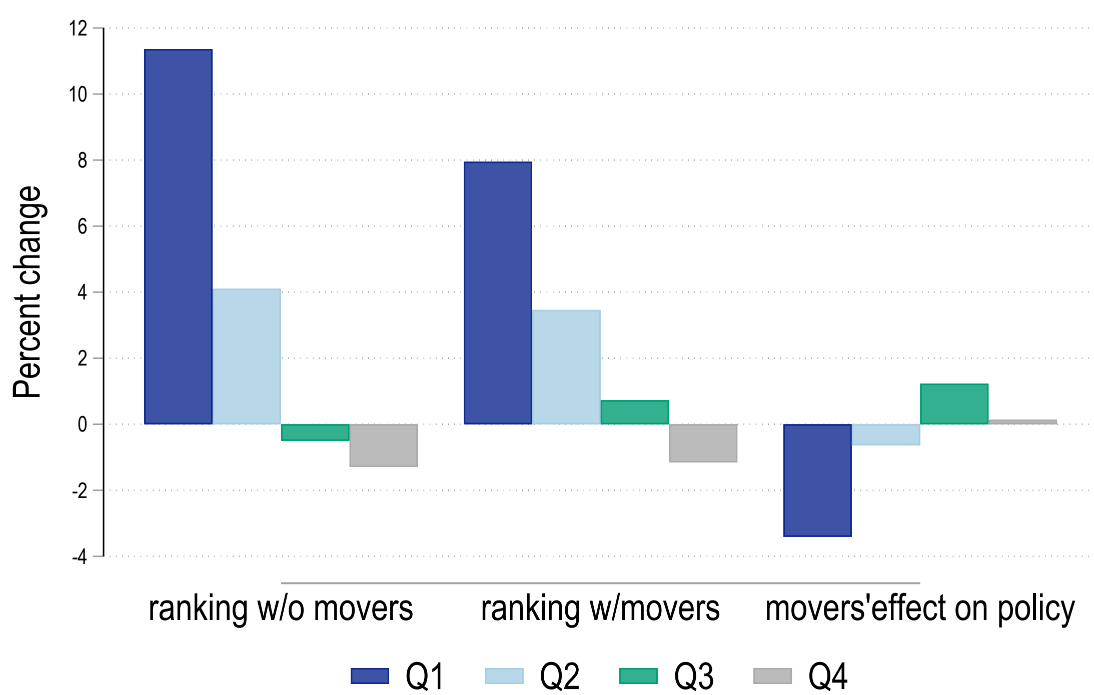
Notes: This figure presents the percent of students with positive potential gain (purple bar) and no potential gain (gray bar) in their choice set defined as a 4 kms buffer with the center in students' primary schools.

Figure 8. Policy effects in cohort applying to college in 2014 by schools' quality.

(a) Acceptance rate in *any* university



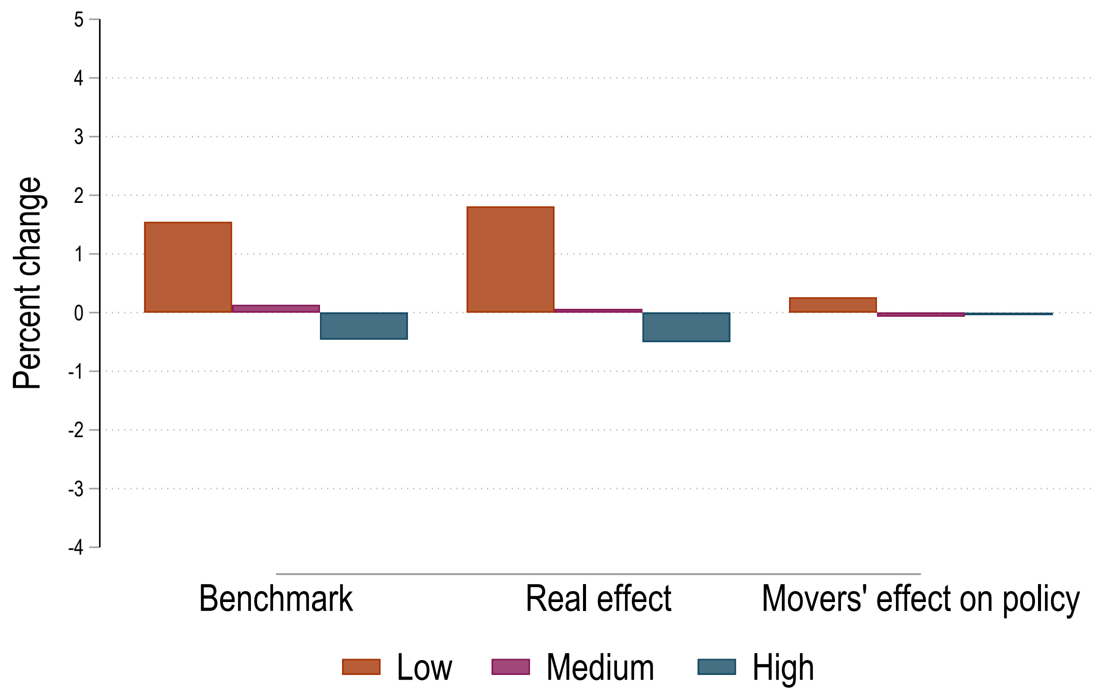
(b) Acceptance rate in *tier 1* universities



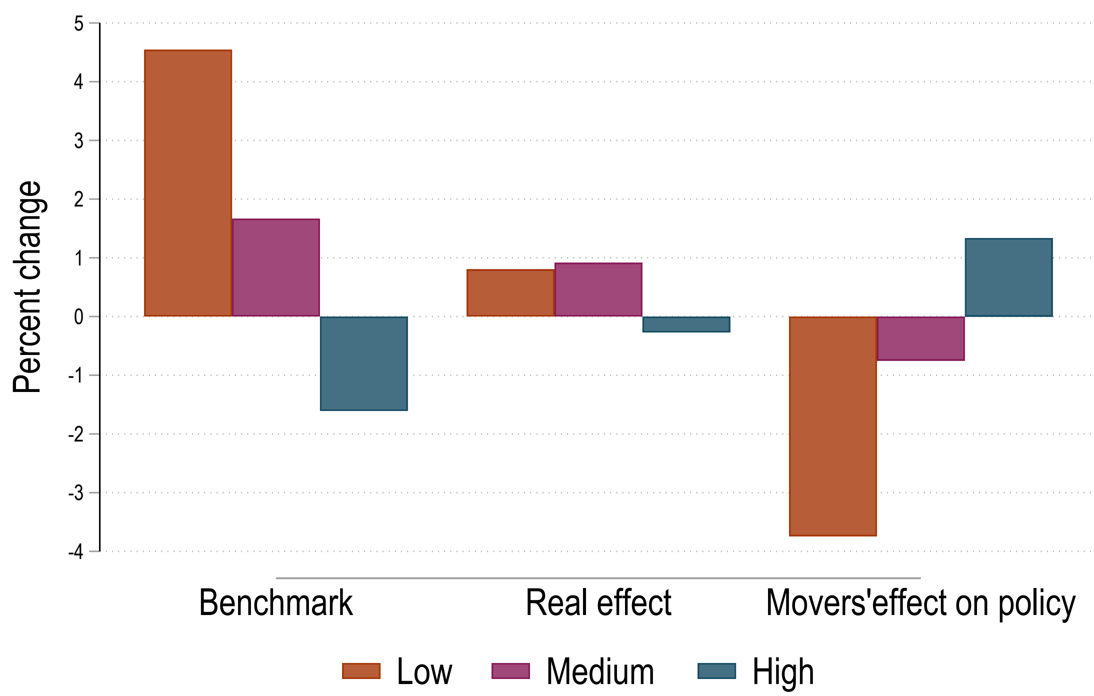
Notes: This figure depicts the percentage change in the number of students accepted in college by school's quality. Denominator in the percentage is the number of students accepted into each category without the policy. Figure (a) presents the changes in rate of acceptance in any university. Figure (b)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

Figure 9. Policy effects in cohort applying to college in 2014 by student's SES.

(a) Acceptance rate in *any* university



(b) Acceptance rate in *tier 1* universities



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

Figure 10. Same thresholds' order

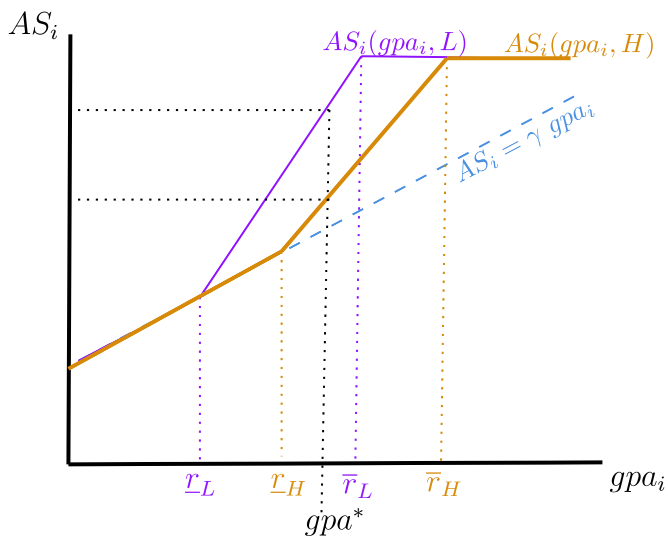


Figure 11. Different thresholds' dispersion

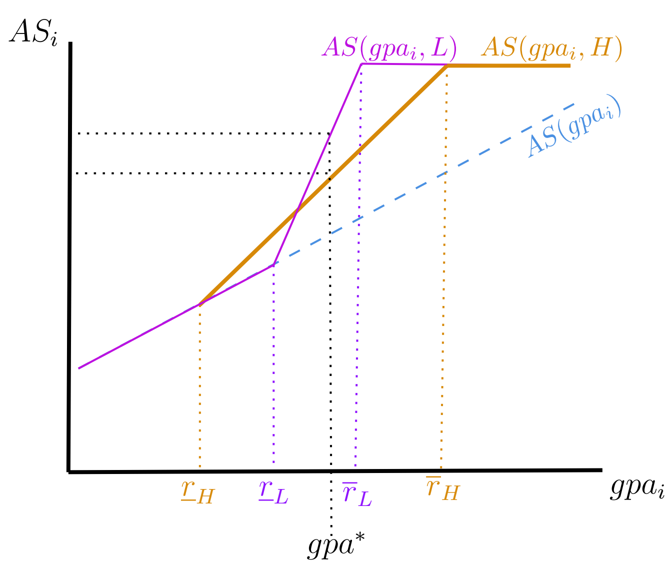
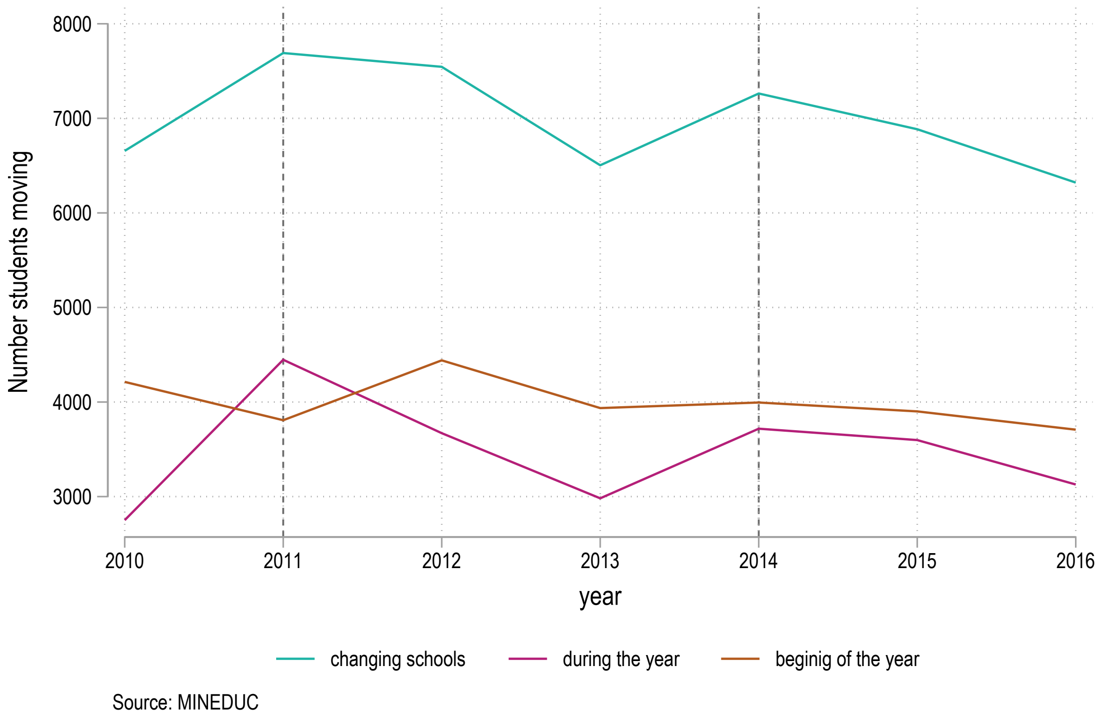


Figure 12. Number of students switching schools in twelfth grade (2010-2016)

(a) *All* students



(b) Students in *top* schools

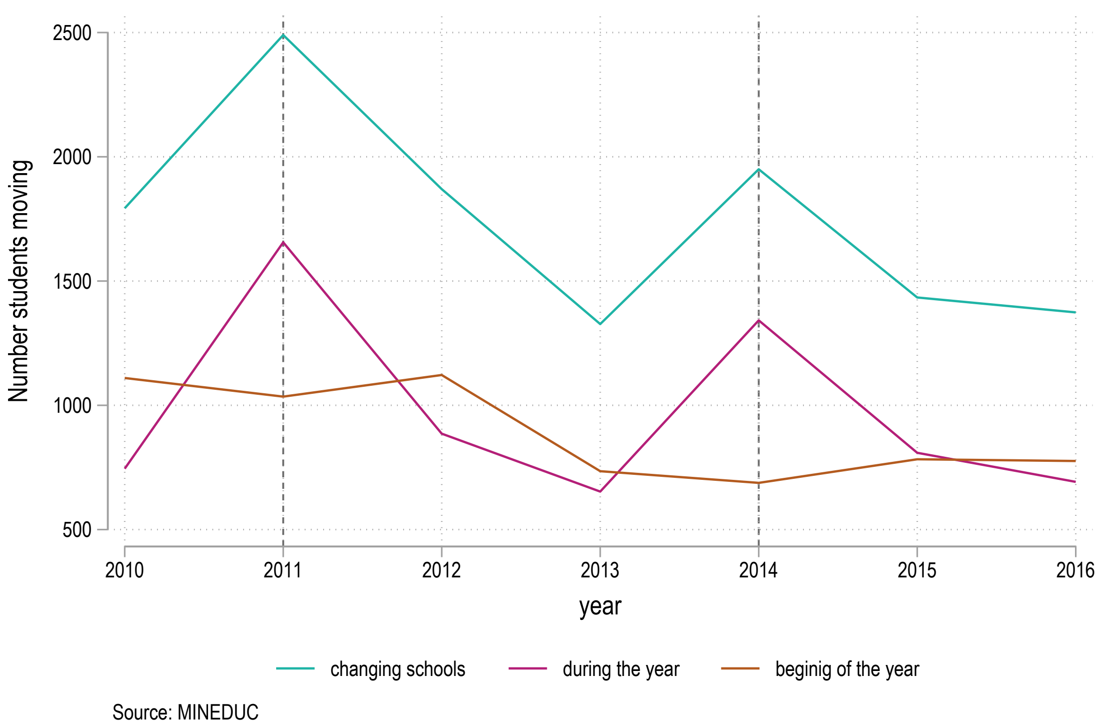
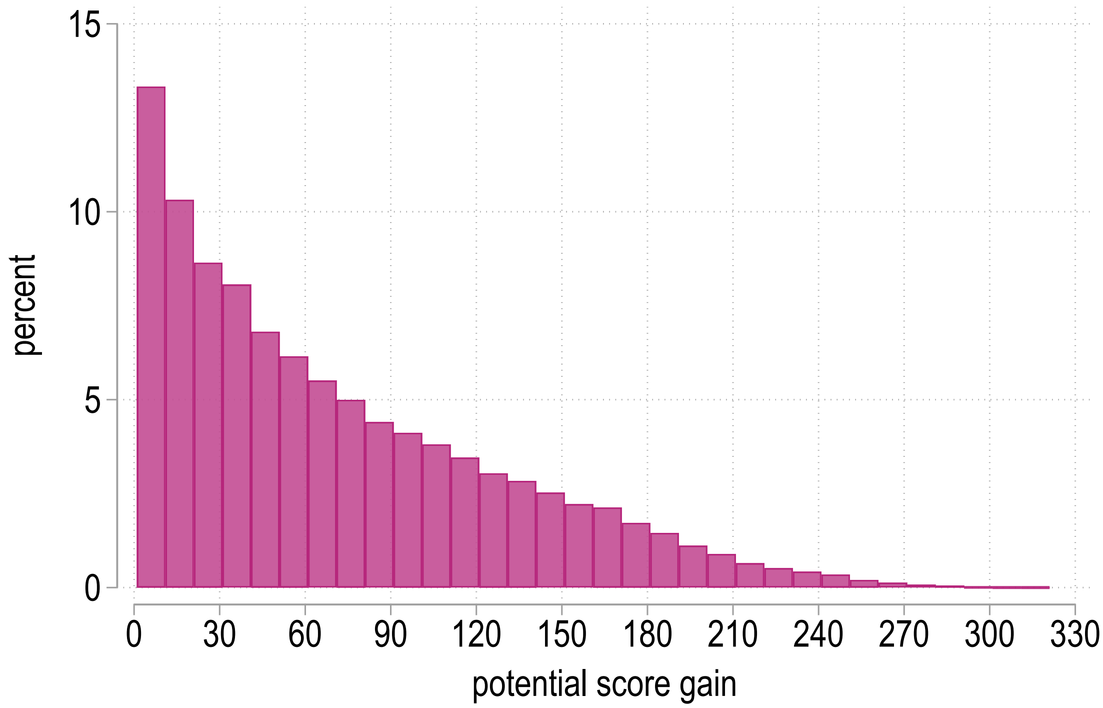


Figure 13. Potential score gain, 4 km buffer (2014)

(a) Distribution



(b) Empirical distribution

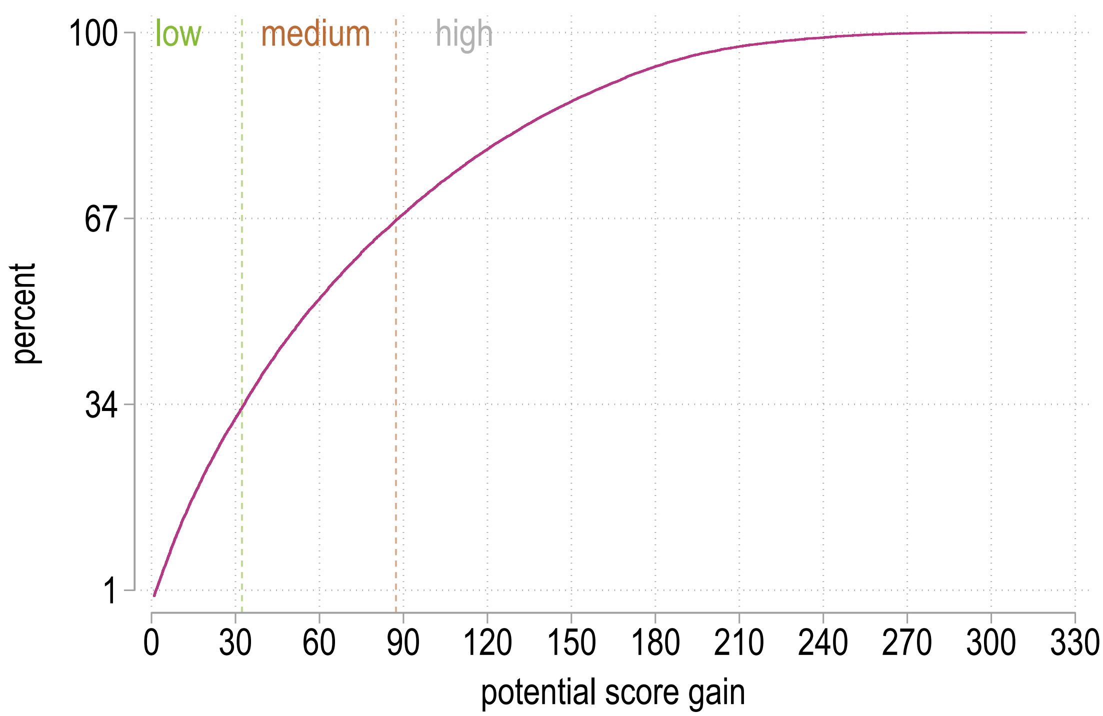


Figure 14. Potential score gain and GPA, 4 km buffer (2010-2014)

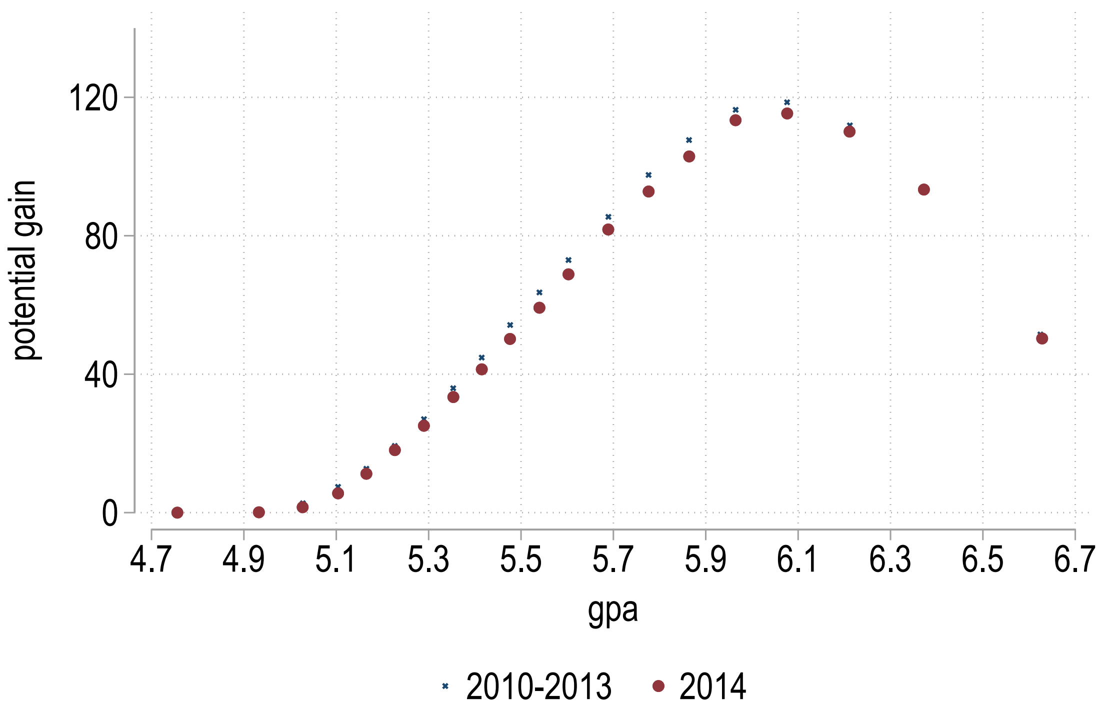
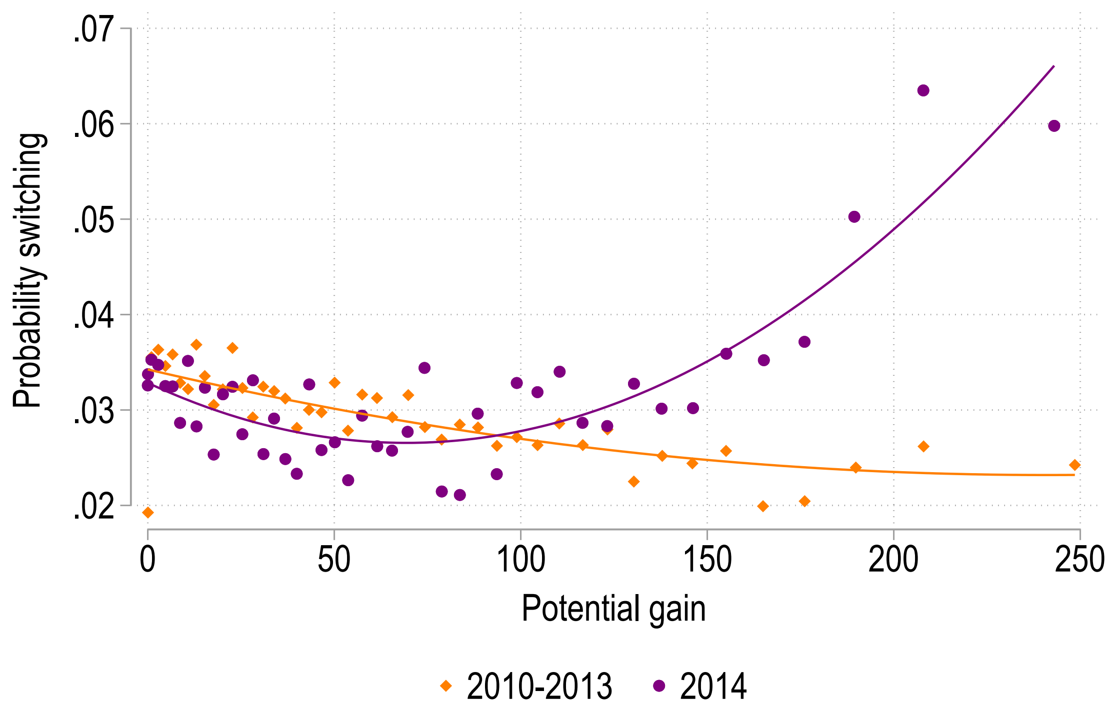


Figure 15. Potential score gain, realized score gain and probability of switching (2010-2014).

(a) Potential score gain and probability of switching schools



(b) Potential score and realized gain

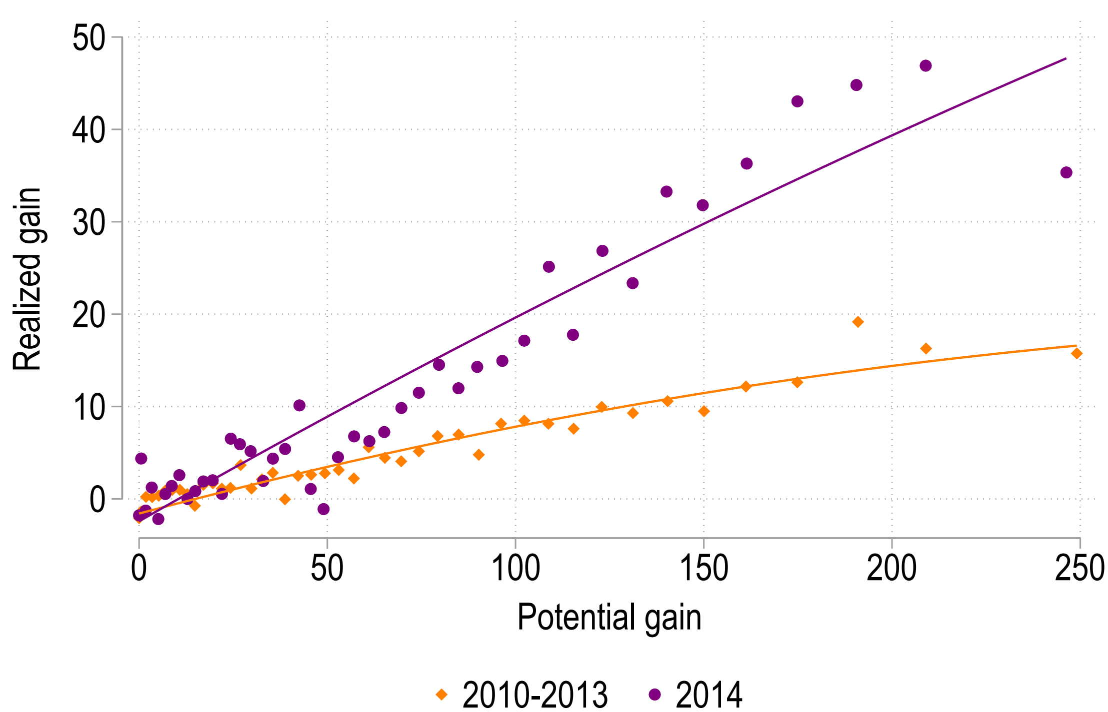
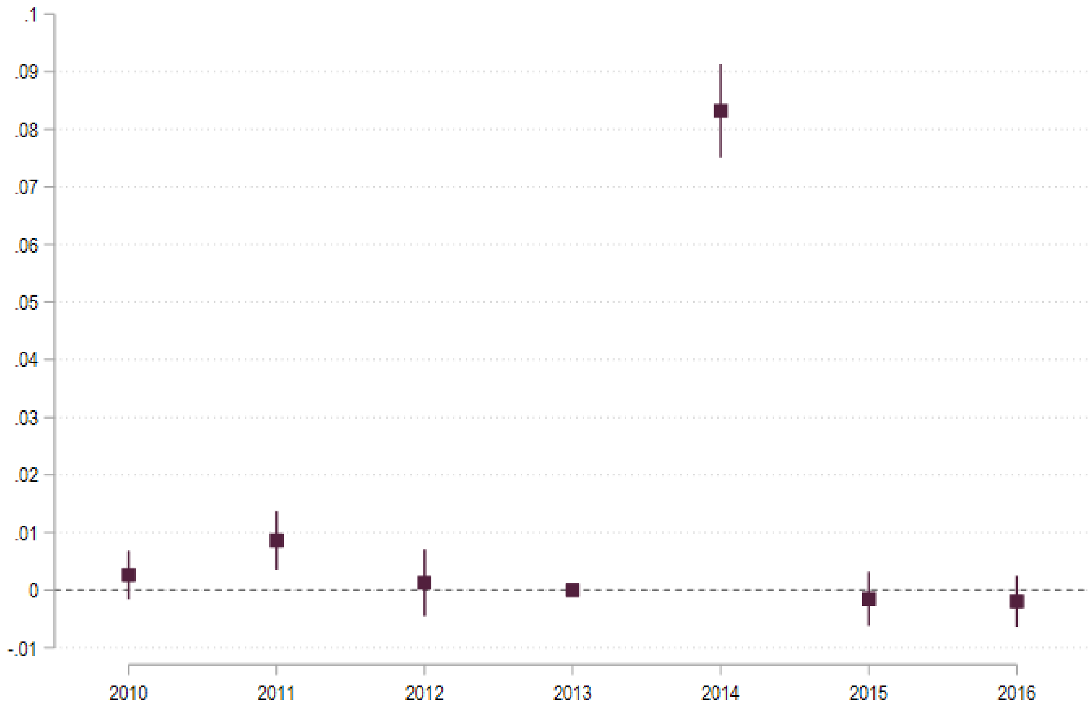


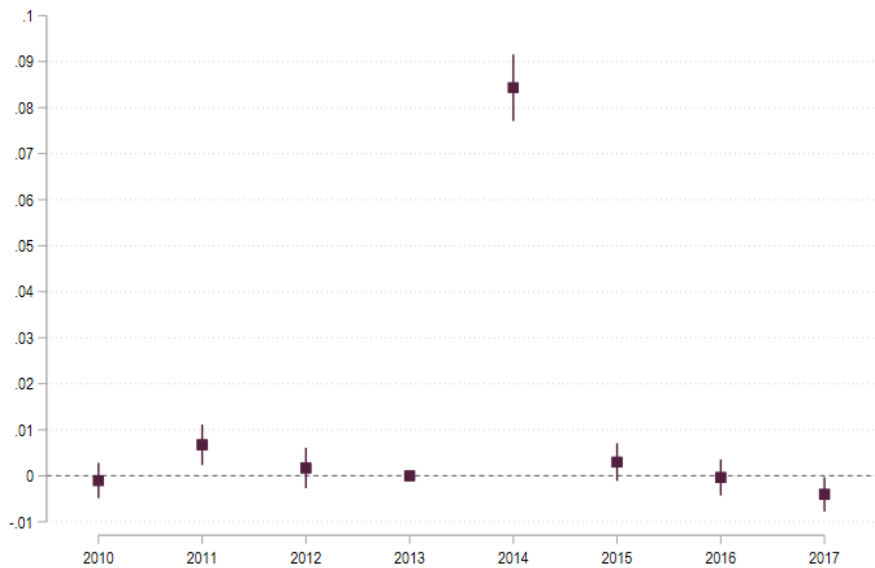
Figure 16. **Probability of switching schools.**



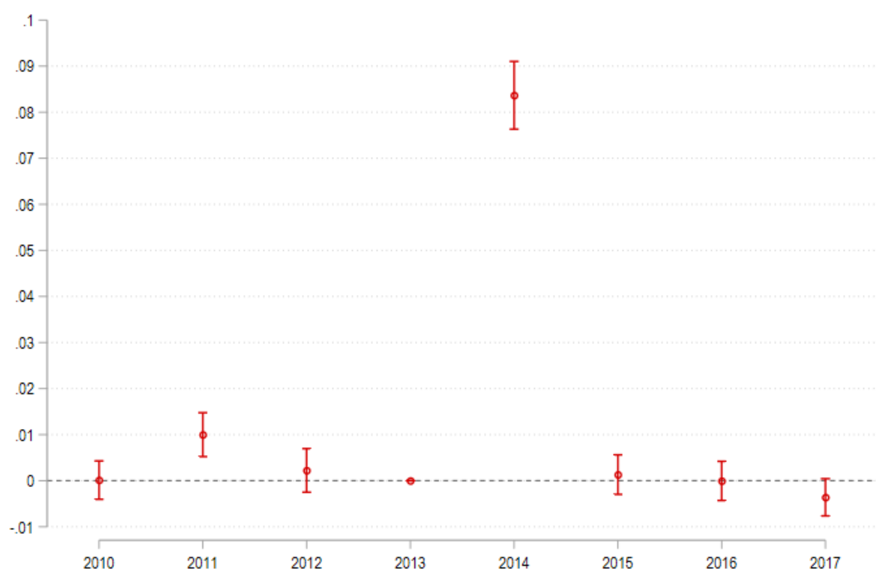
Notes: This figure depicts an event study design for probability of switching school. The coefficient represents the difference in each year in the unconditional probability of switching school for students in elite and non-elite public school in the metropolitan area. *Data sources*: Chilean Minister of Education.

Figure 17. **Strategic switching**

(a) Targeting lower mean thresholds' schools



(b) Targeting schools who sent less number of students to college pre-policy



Notes: This figure depicts the probability of strategically switching school. The coefficient represents the difference in each year in the unconditional probability of switching school for students in elite and non-elite public school in the metropolitan area. In panel (a) the outcome of interest is a dummy variable equal one if student switched school to a lower mean threshold school. Panel (b) considers the results for an outcome variable equal to 1 if students switched to a school sending lower number of students to college. *Data sources*: Chilean Minister of Education.

Figure 18. **Probability of switching schools.**

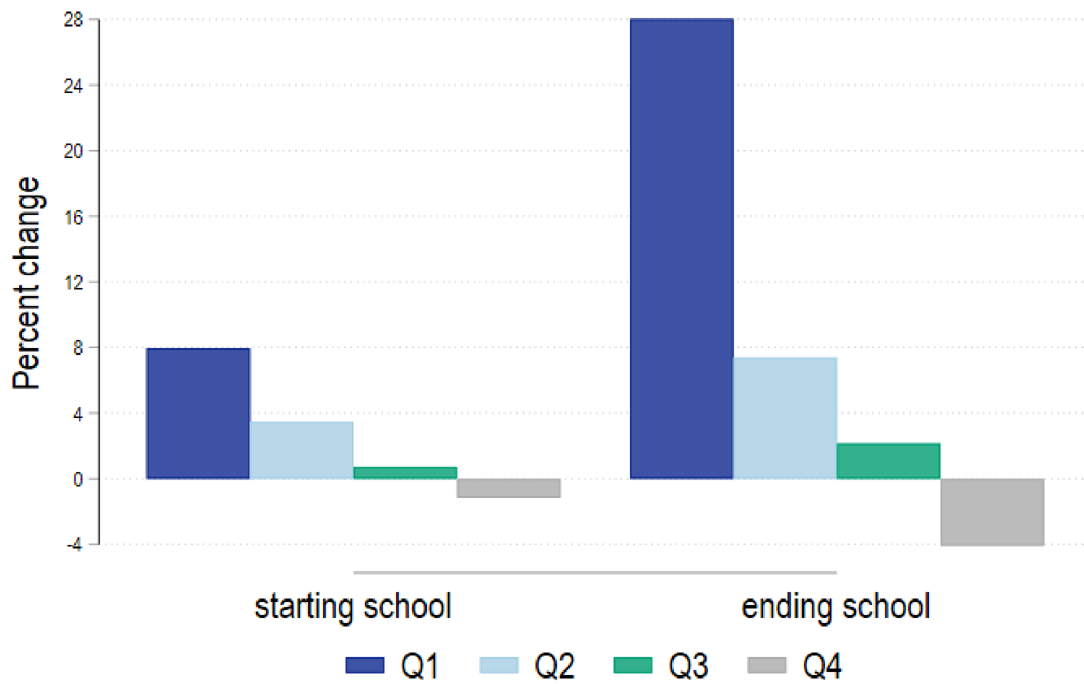


Table 3. **Descriptive Statistics. Students characteristics in universities' acceptance rate (2009-2010)**

	Mean & Standard deviation (1)	Accepted (2)	Tier 1 (3)	Tier 2 (4)
Panel A: *Outcome variables*				
Unconditional mean		0.70	0.15	0.35
		(0.46)	(0.35)	(0.48)
Mean for low SES		0.64	0.06	0.34
		(0.48)	(0.24)	(0.47)
Mean for medium SES		0.69	0.12	0.36
		(0.46)	(0.32)	(0.48)
Mean for high SES		0.77	0.26	0.35
		(0.42)	(0.44)	(0.48)
Panel B: *Students'characteristics*				
High achiever	0.45	0.26***	0.16***	0.04***
	(0.50)	(0.01)	(0.02)	(0.01)
Female	0.51	-0.07***	0.01***	-0.08***
	(0.51)	(0.00)	(0.00)	(0.01)
Low SES	0.25	-0.08***	-0.10***	-0.02**
	(0.25)	(0.00)	(0.02)	(0.01)
Medium SES	0.50	-0.01***	-0.04***	0.01**
	(0.50)	(0.00)	(0.01)	0.01)
High SES	0.25	0.10***	0.16***	0.00
	(0.25)	(0.00)	(0.03)	(0.01)
In metropolitan region	0.32	-0.07***	0.33***	-0.05
	(0.47)	(0.01)	(0.04)	(0.03)
Panel C: *High schools'characteristics*				
Public schools	0.33	-0.03**	-0.09***	-0.05
	(0.47)	(0.01)	(0.02)	(0.02)
Voucher schools	0.53	-0.03***	-0.11***	0.01
	(0.50)	(0.01)	(0.03)	(0.02)
Private schools	0.14	0.11***	0.38***	-0.02
	(0.35)	(0.01)	(0.06)	(0.04)
School's quality 1st quartile	0.06	-0.17***	-0.05***	-0.05***
	(0.24)	(0.01)	(0.01)	(0.01)
School's quality 2nd quartile	0.15	-0.10***	-0.03**	-0.03***
	(0.36)	(0.01)	(0.01)	(0.01)
School's quality 3rd quartile	0.27	-0.02***	-0.02**	-0.02
	(0.44)	(0.01)	(0.01)	(0.01)
School's quality 4th quartile	0.52	0.11***	0.04***	0.04***
	(0.50)	(0.01)	(0.01)	(0.01)
Observations		192,686	192,686	192,686

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

Table 4. **Descriptive Statistics. Students characteristics in potential gain (2014)**

	Mean & Standard deviation (1)	Potential gain (2)
Panel A: *Outcome variables*		
Unconditional mean		73.05
		(59.33)
Mean for low SES		59.01
		(52.73)
Mean for medium SES		71.68
		(58.30)
Mean for high SES		89.55
		(62.37)
Panel B: *Students'characteristics*		
High achiever	0.62	61.23***
	(0.48)	(2.85)
Female	0.55	5.13***
	(0.55)	(0.58)
Low SES	0.25	-19.90***
	(0.25)	(1.71)
Medium SES	0.45	-4.24***
	(0.45)	(1.49)
High SES	0.31	22.36***
	(0.31)	(2.09)
In metropolitan region	0.45	28.32***
	(0.50)	(5.59)
Panel C: *High schools'characteristics*		
Public schools	0.33	-14.70***
	(0.47)	(2.13)
Voucher schools	0.54	-3.33
	(0.50)	(2.77)
Private schools	0.13	35.62***
	(0.34)	(3.94)
School's quality 1st quartile	0.12	-18.09***
	(0.33)	(2.54)
School's quality 2nd quartile	0.21	-8.89***
	(0.40)	(1.45)
School's quality 3rd quartile	0.27	-4.90**
	(0.45)	(2.05)
School's quality 4th quartile	0.40	18.33***
	(0.49)	(2.05)
Observations		125,681

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

Table 5. **Students characteristics by type of gain (2014)**

	Overall (1)	Low gain (2)	Medium gain (3)	High gain (4)
Panel A: *Students'characteristics*				
Female	5.128***	0.553***	0.769***	0.174
	(0.581)	(0.101)	(0.182)	(0.623)
Low SES	-19.905***	-1.027***	-1.485***	-7.459***
	(1.714)	(0.139)	(0.275)	(1.195)
Medium SES	-4.237***	0.117	-0.470**	-1.679
	(1.491)	(0.101)	(0.190)	(1.260)
High SES	22.361***	0.117	1.905***	6.133***
	(2.086)	(0.101)	(0.289)	(1.537)
Has internet	20.831***	1.188***	1.582***	9.307***
	(2.102)	(0.158)	(0.317)	(1.253)
Located in metropolitan region	28.322***	0.446	1.877***	20.927***
	(5.593)	(0.343)	(0.487)	(3.698)
Panel B: *High schools'characteristics*				
$\underline{r}$	65.148***	3.784***	5.375***	18.774***
	(4.697)	(0.670)	(0.885)	(4.303)
$\overline{r}$	71.867***	2.352***	6.349***	28.956***
	(7.827)	(0.569)	(1.323)	(7.908)
Public schools	-14.702***	-0.979***	-1.255***	-3.282**
	(2.134)	(0.191)	(0.343)	(1.587)
Voucher schools	-3.332	0.627***	-0.246	-3.846*
	(2.769)	(0.187)	(0.324)	(2.100)
Private schools	35.619***	1.326***	3.307***	9.392***
	(3.945)	(0.485)	(0.562)	(3.183)
School's quality 1st quartile	-18.086***	-0.749**	-1.033**	-7.141***
	(2.543)	(0.314)	(0.411)	(2.347)
School's quality 2nd quartile	-8.888***	-0.379**	-0.783**	-0.555
	(1.446)	(0.189)	(0.352)	(1.291)
School's quality 3rd quartile	-4.902**	-0.384*	-0.528*	-1.242
	(2.046)	(0.222)	(0.317)	(1.685)
School's quality 4th quartile	18.327***	1.178***	1.448***	3.478***
	(1.504)	(0.210)	(0.397)	(1.233)
Mean outcome: potential score gain	73.05	15.88	59.08	144.21
Observations	125,681	41,900	41,888	41,893

Notes: $^{*}p < .10,^{**} < .05,^{***} p < 0.01$.

Table 6. **Descriptive Statistics. Students characteristics in switching decision (2010-2013)**

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

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

Table 7. **Difference in Difference estimation (2012-2014).**

	2012 vs 2014 (1)	2013 vs 2014 (2)
Panel A: *Students'characteristics*		
Female	0.300	0.198
	(0.497)	(0.380)
High aspirations	0.875**	
	(0.385)	
Medium SES	0.874***	0.956***
	(0.282)	(0.291)
High SES	0.761**	1.222***
	(0.352)	(0.330)
Panel B: *Schools'characteristics*		
School quality: Q2	-0.195	0.120
	(0.574)	(0.378)
School quality: Q3	0.043	0.399
	(0.556)	(0.402)
School quality: Q4	1.584***	2.343***
	(0.540)	(0.576)
Public schools	4.695***	4.079***
	(1.536)	(1.153)
Voucher schools	-0.580*	-0.440
	(0.350)	(0.279)
Number observations	145,985	167,536
Number schools	2,250	2,247
Mean outcome	2.209	2.041

Notes: $^{*}p < .10,^{**} < .05,^{***} p < 0.01$. .

Online Appendix for:

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

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

In Chile every year, before grade twelfth finishes, students have access to the main information required to succeed in their application to college.[50] In the main website that CRUNCH has created for the national standardized test (NT), they can access to several information: preliminary list of majors, number of slots and weights used for each requirement (released at the end of May), main material that will be cover in the standardized test (beginning of June), normative, inscription process to take the test, and main aspects to consider when taking the NT and applying to college (end of June), main information about the universities using the centralized system, such that, departments, statistics about: students enrolled and graduated the previous year, professors' degrees, research investigation active at the moment (beginning of August), final version of majors available by university, their weights in all the requirements, slots and other general advise (end of Sept./beginning of Oct.), locations where each student will take the NT (beginning of Nov.), benefits, scholarship and other services (end of Nov.), and enrollment instruction (beginning of Dec.).[51]

I argue in the main text that students switching decision in 2014 and not in the previous years happened because of the timing of the relevant-to-this-decision information. Here, I discuss in more detail how this happened. Although the RR policy was implemented at the end of the academic year 2012, therefore applicable for the 2013 college admission process, that year all the universities adjusted the weights by subtracting ten percent from the GPA requirement. This change could not affect switching decision in the 2012 year, since it was informed in November, last moth of that academic year. Although students could have switch the next year, the small weight did not make the policy salient enough.

[50] See here for the 2023 application process.
[51] See here for the 2015 application process.

In 2013, year where the weight to the RR increased to an average of thirty percent, students received this information in November of that year, not in the preliminary information released in June, as usual.[52] This made impossible for students in grade twelfth to switch during this year. Therefore, students starting grade twelfth in 2014 are the first cohort with incentives to switch due to this policy, its implementation and its calculation.

B Model Derivations and Proofs

Proof. Proposition 1.

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

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

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

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

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

Now, by the unique application score constraint we have

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

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

Now, since AS does not depend on where student graduated, there are not incentives to relocate. Finally, from the capacity constraint we have

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

[52] For more information see here.

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

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

Similarly for school L. □

Proof. Proposition 2.

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

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

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

Assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L \leq \overline{r}_H$, then for any student with $gpa \in (\underline{r}_L, \overline{r}_H)$ the application score graduating from school L is higher than when they graduate from school H, $AS_L(gpa) > AS_H(gpa)$. Now, using Constraint 1, we know that in equilibrium

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

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

Using Constraint 2 and imposing no switching, we have

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

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

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

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

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

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

Because $gpa^*_{L,1} \neq gpa^*_{H,1}$, it must be true that one school gain and the other lost in terms of acceptance rate. If $gpa^*_L < gpa^*_H$, school L gains and school H lost. Because students are not allowed to move, then $\mu_L\big[G_L(AS_L(gpa^*_{L,1})) - G_L(AS(gpa^*_0))\big]$ and $\mu_H\big[G_H(AS(gpa^*_0)) - G_H(AS_H(gpa^*_{H,1}))\big]$ represents the change in the composition of accepted students into college in terms of school of origin.

Now assume $\underline{r}_L < \underline{r}_H$ and $\overline{r}_L > \overline{r}_H$. Then for any student with $gpa \in (\underline{r}_L, r^*)$ the application score graduating from school L is higher than when they graduate from school H, $AS_L(gpa) > AS_H(gpa)$. When $gpa \in (r^*, \overline{gpa}_L)$, the application score in school L is lower than in school H,$AS_L(gpa) < AS_H(gpa)$ (see Figure 11). Now, using Constraint 1, we know that in equilibrium

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

Let AS^*_1 be the unique cutoff in equilibrium after the policy is implemented but students are not allowed to switch. Since $AS^*_1 = AS_L(gpa^*_L)$, then $gpa^*_L = AS_L^{-1}(AS^*_1)$, and $gpa^*_H = AS_H^{-1}(AS^*_1)$. Therefore $gpa^*_L < gpa^*_H$ when $AS_L(gpa) > AS_H(gpa)$, and $gpa^*_L > gpa^*_H$ when $AS_L(gpa) < AS_H(gpa)$.

Similarly than before, from Constraint 2 we have

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

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

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

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

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

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

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

with $AS_L(gpa) \neq AS_H(gpa)$ for any given GPA. From Constraint 2:

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

Notice that one of the two last lines are *effective* for any combination of application score in school H and L.[53] Suppose $d_H = 1$, then the capacity constraint is

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

Simplifying a little:

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

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

$$\mu_H G_H(AS^*_0) + \mu_L G_L(AS^*_0) = \mu_L \cdot G_L(AS_L(gpa^*_L)) + \mu_H \cdot G_H(AS_H(gpa^*_L))$$

Which is true when $gpa^*_0 = gpa^*_L$, therefore the pool of students accepted into college did not change.

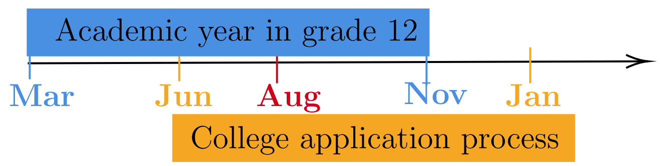
Finally, suppose a fraction q of students with a potential gain in switching, have a cost of switching higher than the value of college. Then only that fraction of students switch schools, and therefore the pool of accepted students into college change in a ratio equal to $1 - q$.

□

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

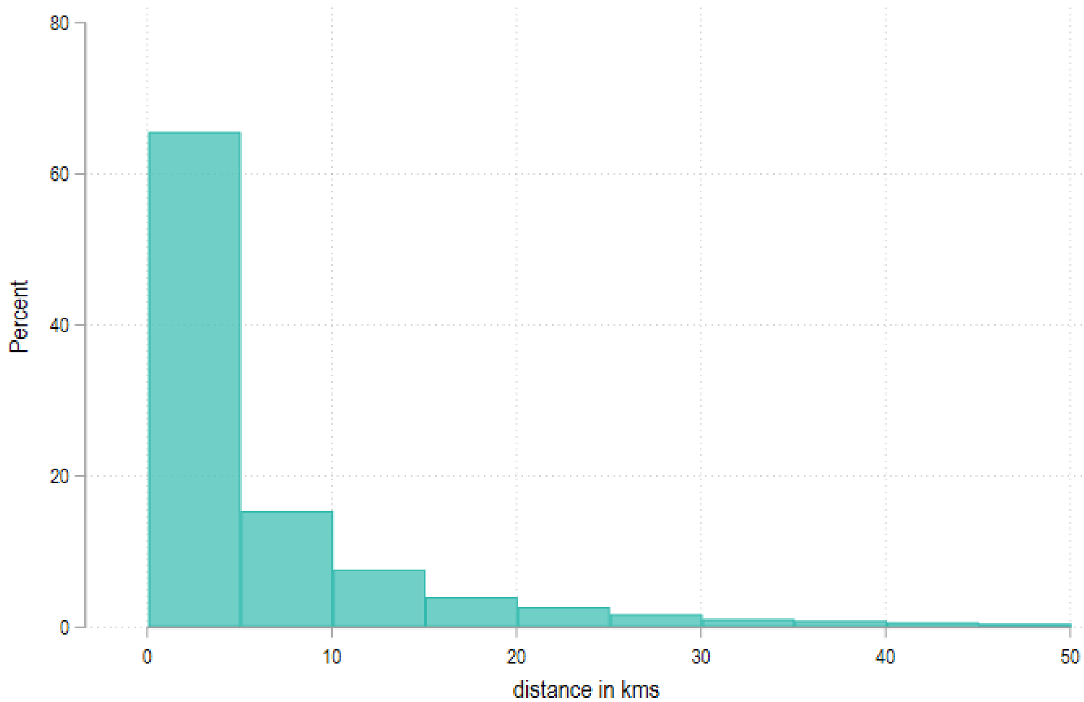
C Additional tables and figures

Figure C.1. Academic Year and College Application Timeline



Notes: This timeline shows initial and final months for the academic year in grade twelfth (blue) and the college application process (orange). August is the last month students can opt to switch schools (starting in the new school in September).

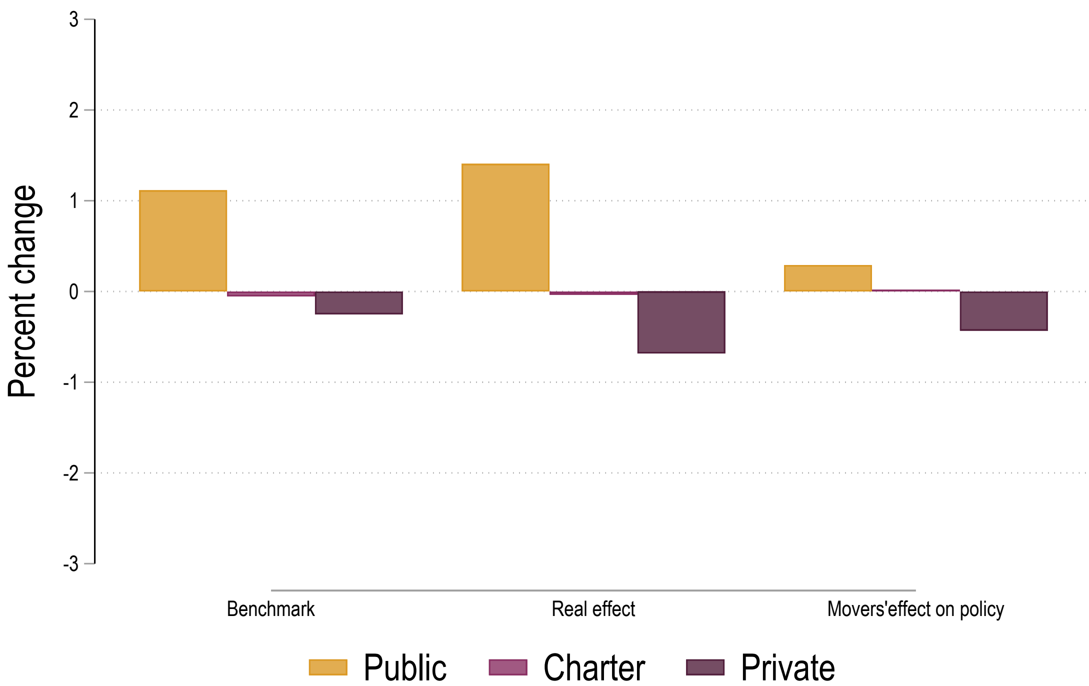
Figure C.2. Distance in kilometers between student's primary and secondary school (2014).



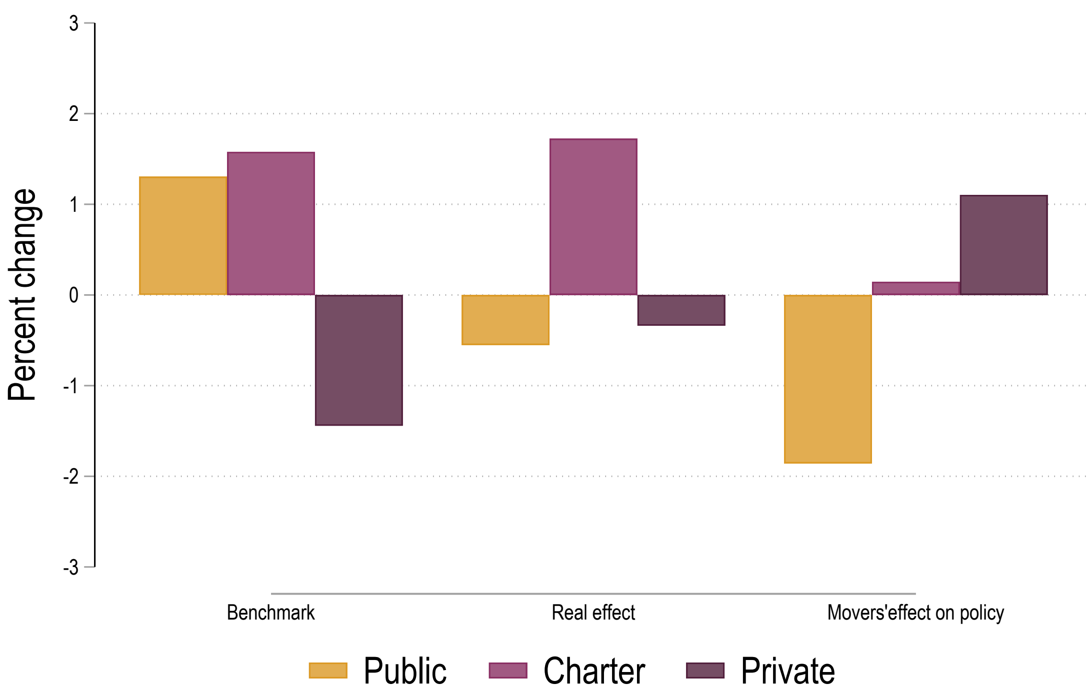
Notes: This figure presents the distribution of real distance in kilometers for students' initial school in grade twelfth with respect to their primary schools. I exclude here students who are in the same school than primary school since the distance in that case is zero. More than seventy percent of students population are consider in this sample.

Figure C.3. Policy effects in cohort applying to college in 2014 by type of school.

(a) Acceptance rate in *any* university



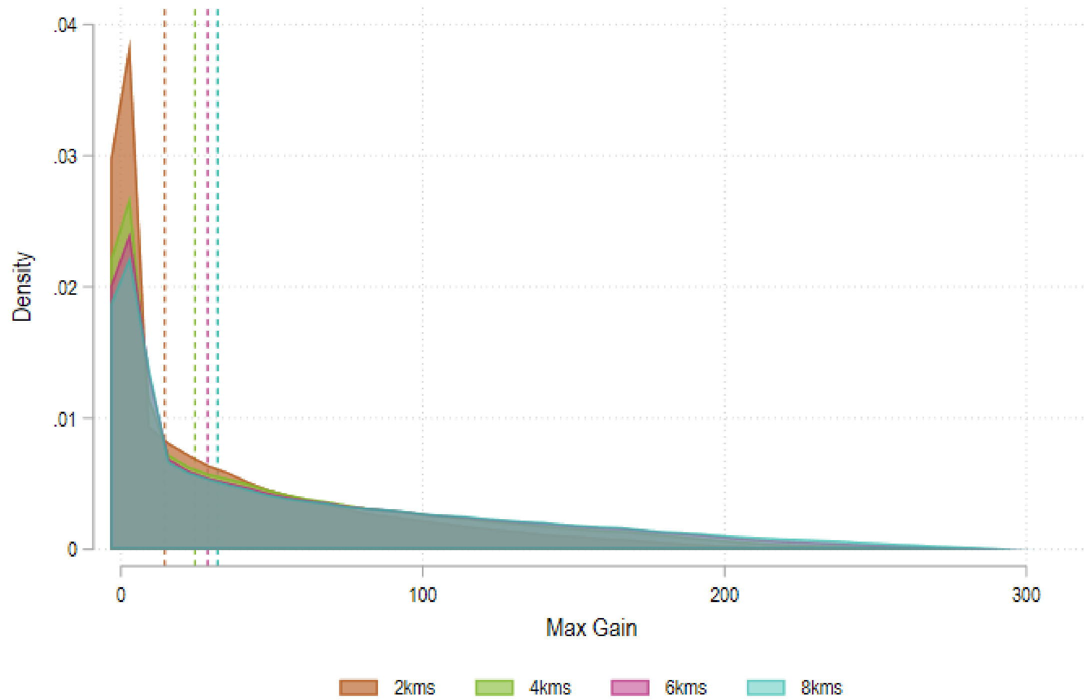
(b) Acceptance rate in *tier 1* universities



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

Figure C.4. Distribution student's maximum potential gain

(a) Using student's primary school as buffer's center



(b) Using student's high school as buffer's center

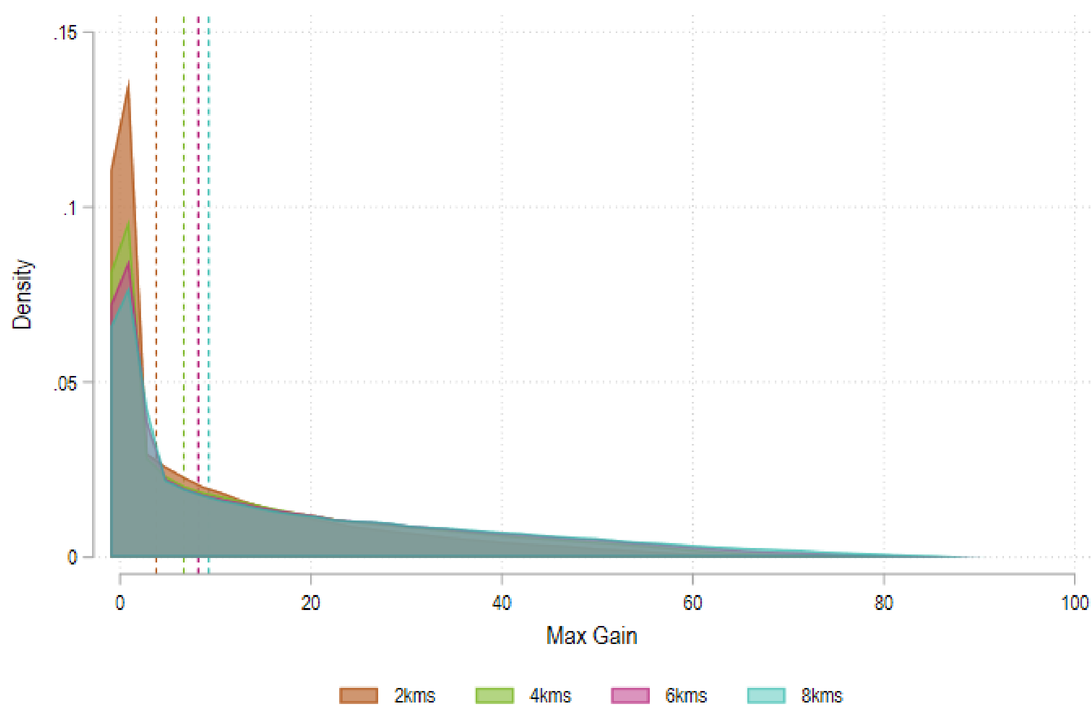


Figure C.5. Average number of slots in the system (2010-2015)

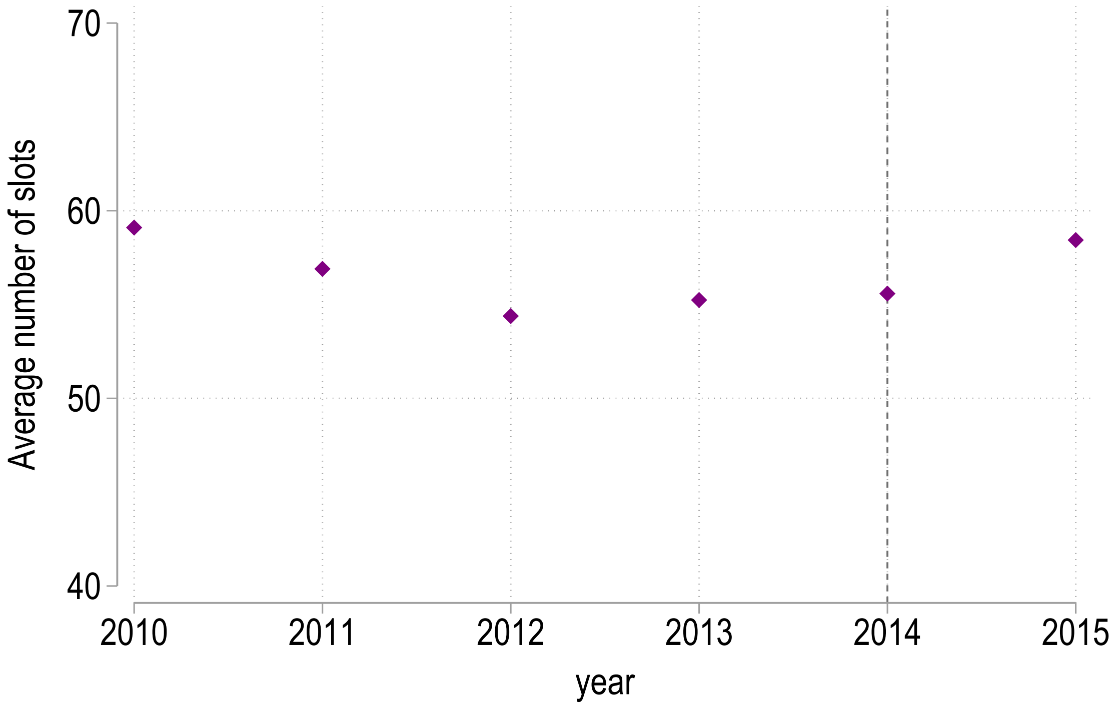


Figure C.6. Ratio accepted over applying to college (2010-2015)