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

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Abstract

Policies aimed at increasing the number of students from underrepresented groups enrolled in college are common worldwide. Yet, little is known of their pre-college effects or if these effects meet policies' goals. This paper asks whether centralized college admission policies that rank students within their high school lead to high school students changing schools to gain an advantage. Additionally, I calculate the effect of relocation on the effectiveness of the policy. Relying on a policy change in Chile and using detailed administrative data and a simple theoretical model, I show that high school students react to these sorts of college admission policies by switching schools, undermining the policy effects. I find that the number of low-income students accepted into the top colleges increases 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 relocation is an important pre-college response, which needs to be considered when designing policies using schools as the main students' characteristic to equalize opportunities, as it can completely undermine said policies.

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1 Introduction

The low level of college access for disadvantaged students has long been a concern among academics and policymakers worldwide.[1] 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 among the wealthiest quintile (UNESCO). 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).

Many governments have policies influencing college admissions to alleviate inequality in college access. One of the most popular but also most controversial policies is the special consideration of certain groups when applying to college, known as affirmative action (see Arcidiacono et al. (2015)).[3] One big challenge when using affirmative action or other policies addressing inequality in access to college is reactions from those who are not targeted by the policy and who often see themselves as actually 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 their increasing popularity, evidence of how such policies affect K-12 school choice is limited (Cullen et al., 2013; Mello, 2021; Estevan et al., 2018).

In this paper, I study how students' pre-college reactions to the college admission

[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 strata of society (UNESCO).

[2]Policies vary from special consideration to a given group during the application process (affirmative actions, positive discrimination, or quotas), financial aid, to simply providing information about how to apply to college and the benefits of attending.

[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 the University of Texas; Brazil, where federal universities implemented quota laws; and Chile, which incorporated a measure to compare a given student's GPA to historical trends in their high school.

[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 will hear the arguments in the SFFA v. Harvard University case at the end of October 2022, where SFFA seeks to ban Harvard's race-conscious admissions. One of this case's main characteristics is that affirmative action hurts Asian-American students who belong to a disadvantaged group.

system affect the performance of the policy in meeting its goal. I study this issue in the context of Chile. I leverage the release of information about a new criterion added to the application score in the centralized college admission process.[5] This score was previously based on students' high school GPA and a standardized test score. The new measure is based on students' relative high school performance (relative ranking or RR), such that students get a higher score if their GPA is above the mean of the three previous cohorts in their school, creating incentives for students to choose a high school not only on the quality of education they will receive or other personal needs but also maximize their relative ranking and thus their probability of being admitted to their chosen college.

Chile is an informative setting for this analysis for several reasons. First, a major challenge in studying affirmative action policies and high school students' strategic responses is the lack of detailed records in K-12, students' applications, and pre-college decisions together. Chile has extensive detailed administrative data on both K-12 education and the college application process, overcoming this problem (Bodoh-Creed and Hickman, 2018). Second, Chile's RR policy belongs to a centralized system, with clear admission rules, an application score formula, and applicants' preferences over major/college combination,[6] which helps researchers evaluate the policy's effects under different circumstances. This type of admission system has been used around the world not only for higher education; the number of countries using centralized admission has more than doubled since the nineties (Neilson, 2019). Finally, part of the Chilean educational system features the fact that students can relocate to schools easily and up to 3 months before the academic year ends.[7]

For this paper, I create a unique data set to characterize the population switching high schools due to the policy and the impacts of these decisions on several outcomes of interest, such as college acceptance rate by students' socioeconomic backgrounds. First, I combine several administrative records containing students' 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

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

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

[7] In Chile, students do not need to study in public schools that are in their municipality, similar to voucher schools.

admission offers, among other factors. Finally, I incorporate information from a paired standardized test and survey taken in tenth grade (SIMCE) that contains 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 the representation of historically disadvantaged populations and communities.

In the first part of the paper, I exploit the clear application score formula and the college-student matching algorithm to study the effects of the policy. By simulating the changes in the pool of accepted students considering the formula before and after the policy, I can compute the change in the acceptance rate for low-SES students and schools' quality. In contrast with the policy's goal, I find that the increase would have been about 5% if students did not switch schools, while the real effect is around 0.5%. When considering schools' quality, I find that students from low-quality schools are 8% more likely to be accepted into selective colleges. However, the effect could be as high as 12%, representing a drop of 25% in the policy effectiveness. These results have been considered by the government as modest results (Larroucau et al., 2015). My results are in line with effects previously found by Kapor (2015) in the case of Texas Top Ten Percent law, a policy giving guranteed access to public universities in Texas for high achieving students from public schools.

To better understand the small effects of the policy, I analyze, theoretically and empirically, how switching high schools may be affecting college acceptance rates. I build a simple school choice model where students decide whether to switch high schools while taking the college application cutoff as given. This model has three main insights. First, the effect of the policy, specifically changes in the acceptance pool, depends on students' costs from switching high schools. When the relocation cost is high, the policy is more successful in terms of increasing the acceptance rate for low-quality schools. 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-quality schools are the most likely to benefit from switching high schools since those schools have higher GPA thresholds.[8]

The second part of my paper then addresses which students increase their application scores by switching schools and how many of those students took advantage

[8] Although this is a theoretical assumption in my model, I test it in the data and find support for it.

of the policy. To evaluate the application score changes due to school switching, I take advantage of the RR policy information released and its clear rules. I calculate each student's application score for all schools they could switch to. I then take the highest score increase they would have (*potential gain*). Using this variable, I show that: (i) the realized and potential gains are positively correlated, although students did not get the maximum increase when actually 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 heterogeneities in switching cost, the value of high schools and/or attending college.

Given that not all students could benefit switch schools, I characterize students switching schools the year the information was public (2014). To do so, I calculate students' application score gain they would have before 2014. Using a difference-in-difference design, I exploit the variation in the information released and students' predetermined characteristics to show that within schools, students from high SES backgrounds and with high aspirations[9] increase their likelihood of switching schools by 0.8 percentage points (relative to a 2.2 percent probability). Further, students starting the academic year in high-quality or public schools are also more likely to switch post-policy.

Finally, motivating by my previous finding and taking advantage that students' initial school's quality was predetermine to the policy, I use students' initial school's quality to estimate the changes in their likelihood of switching schools. Here, I use an event study design comparing students who started twelfth grade in a high-quality school with their peers in non-high-quality schools yearly from 2010 to 2016 with respect to 2013.[10] I find that students who started in elite schools are 8 percentage points more likely to switch in the year the policy was introduced. Furthermore, when analyzing heterogeneities by school type, I find that the increased likelihood of switching is entirely driven by students in elite public schools.[11]

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,

[9]I measure aspirations using parents' answers to a survey they have taken while students were in grade 10.

[10]I rank schools by types: public, charter, and private, using the average score of a standardized test taken by students in tenth grade in 2006.

[11]These schools are highly competitive, and their students rarely switched schools before the policy.

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), and race-segregation levels in high school (Estevan et al., 2018). I contribute to this literature by presenting evidence that non-targeted students change their behavior when college admission policies reward students differently depending on their context by switching schools in grade 12.

A closely connected literature studies affirmative action's impacts on school choice (Cullen et al., 2013; Mello, 2021; Estevan et al., 2018). They examine switching decisions due to affirmative action policies in the context of Texas (US) and Brazil. These papers find, similar to this one that students react to affirmative action policies based on high schools that give direct access to public colleges (Texas Ten Percent Law) or benefit them with a different cutoff for federal universities (the case of Brazil). Relative to these papers, I am able to: (i) estimate the changes in the likelihood of switching schools for students with different characteristics; and (ii) quantify, via simulations, what would be the policy's effect on the overall system and on admission to selective colleges, either public and privates, if students did not have the ability to switch high schools. 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 begging and end of each academic year.

Additionally, I contribute to the literature estimating the effects of different admission policies. This strand of the literature has shown that the context and the design can 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 policy's 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 and calculating the effect of these responses on the policy's effectiveness. From this strand of the literature, Reyes (2022) is closely related to this paper since she evaluates the effects on college enrollment, graduation, and labor outcomes for the Relative Ranking policy in Chile for the year where there was no incentive to switch. I complement her analysis by focusing on pre-college responses to the policy and its effects on college acceptance rates for the entire system and the most selective schools. Similarly, we both rely on the application score algorithm to evaluate the policy effects, although leverage different periods of the policy.

My results also add to the large literature investigating the school characteristics valued by parents and students (Abdulkadiroğlu et al., 2020; Abdulkadiroğlu et al., 2017; Angrist et al., 2013; Haeringer and Klijn, 2009; Rothstein, 2006; Epple et al., 2004; Beuermann et al., 2022), e.g., high-stake exams, peer quality, college attendance, earnings, and crime. My paper contributes to this literature by presenting evidence that parents do value a type of school effectiveness but not one that is measured by say test scores. Since low-quality schools offer a better chance of getting into the desired college program.

Finally, this paper adds to the literature evaluating the effects of relative grades in students' outcomes (Calsamiglia and Loviglio, 2019; Elsner and Isphording, 2017; Diamond and Persson, 2016; Rangvid, 2015). In line with previous findings, I show that better-quality schools lead to lower scores for many high-achieving students, which in turn affects students' college admission scores, leading them to switch to lower-quality 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 presents the results of the policy by schools' quality and students' socioeconomic backgrounds. Section 5 gives a stylized model for understanding the incentives to switch 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 increase low-income students' college acceptance rate. Finally, section 9 provides the final remarks.

2 Institutional Background

Although Chile is a middle-income country with a GDP per capita close to 14,750 USD in 2019,[12] income and education inequality in the country remains high. Estimations from the World Bank for 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 inequality in access to college results are similar; in 2019, 85.2% of adults between 25 and 34 years old finished at least high school, but only 33.7% attained a higher education

[12]Source: World Bank.

degree. Moreover, Narayan et al. (2018) ranks Chile among the least mobile countries in the world, using the share of individuals in the 1980s cohort who are born into the bottom half and who have reached the top quartile.

2.1 Secondary Education in Chile

Chile has had mandatory schooling for primary school since 1965,[13] and high graduation rates in secondary school.[14] [15] A key characteristic of the educational system is the high degree of choice within and between free public, private voucher, and private non-voucher schools for primary and secondary education.

Despite the variety of schools and 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 estimated school quality,[16] 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 mother's education level. We see that students whose mothers have less than high school diploma tend to perform worse, on average, than students with mothers with higher levels of education. The mean performance does not change much for this group of students when we compare the results in tenth and twelfth grades, it worsen for students whose mothers have high school diploma, and improve for students with more educated mothers.

The connection between the quality of schools, 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.[17] 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 paperwas designed to increase equality of opportunities for all (see Section 2.4 for more details).

Students in Chile usually start classes at the end of February or beginning of March

[13] Source: Congreso Nacional de Chile.

[14] Since 2003, attending four years of secondary education has been compulsory for students aged 14 to 17.

[15] In 2019 the dropout rate for any grade between 9 and 12 was less than six percent.

[16] I consider school quality broadly here, including all the inputs that a student receives while spending time in a particular school.

[17] The current president of Chile was one of the leader of this movement. See: The Guardian.

each year, and end second week of December. However, for students in twelfth grade the relevant timeline starts in March, with the beginning of the academic year, and ends in January of the following year, with the enrollment in the matched college-major of their preferences. The key months during college application process are June, when the application information is released, August, 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.

2.2 Tertiary Education in Chile

Universities rank applicants in the centralized admission system using an application score (AS). The AS is a weighted sum of the national standardized test (PSU), student's 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 in 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 the 2022 THE ranking,[20] Pontificie Universidad Catolica and Universidad de Chile ranked first and seventh, respectively.[21]

[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.

2.3 Application to College

All the students who desire attending 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 middle/end of December and, (iii) apply to the ten most preferred majors-colleges 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]

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 to 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, from the applicant pool between 2010 and 2014, twenty three percent of the students are not accepted in any of the universities they have 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

[22]The centralized system calculate 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 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 and Rios (2020).

reports the fraction of students listing 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 an information about each university who uses the centralized admission system.[25]

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 criteria 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, that is 850 points.

Figure 2 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.

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

To understand why students may have an incentive 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 the 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 throughout high school (see figure 3 and appendix A for more details).

Figure 4 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 score derived only from graduating in 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 include 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

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

[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.

other sources: (i) administrative data from the Education Quality Measurement System (SIMCE), (ii) detail 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 analyse 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 characterize students who behave strategically to gain the policy by switching schools. This dataset contains students initial and final schools in grade twelfth between years 2010 to 2014, schools characteristics, such that, ranking, number of teachers, total enrollment and school type (public, charter, private), students characteristics, e.g. gender, age, municipality of residency.

I merge these dataset with tenth grade's standardized test scores and surveys to incorporate more students characteristic, 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 take the switching decision, we would expect that some self-reported characteristics, like 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. Current available records present self-reported information for income in brackets only. This information is used in the college admission process to access to scholarships and loans, therefore one could be concern that there is a measurement error biasing the observed income variable in my dataset. Specifically, we could expect that this variable is under-reported from students since they get financial aid depending of this variable. To overcome this problem, I use students' mother education as a proxy. There are at least two advantage of using this variable instead of income. First, financial aid is not tied to mother's educational outcome. Second, I

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

combine the self-reported mother education variable at the end of grade twelfth with a survey parents answer in grade tenth. I lack information to check the correlation between student's 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 5 presents the correlation between mothers' education and schools' vulnerability index in 2010. The raw correlation between the percent 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 student's primary school location 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 distance between student's 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 for 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 have a small effect increasing low-SES students' acceptance ratio with differential effects depending how selective colleges are. When considering school quality, the policy had a smaller effect that could have if students did not switch school, reducing the effect to 2/3 of the expected results.

[29] The idea behind this proxy bases in the connection between distance to school and families school choice find in the school choice literature focused on primary schools (Neilson, 2013; Allende, 2019).

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

4.1 Descriptive statistics

Table 3 present main characteristics for cohorts graduating between 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 students attend public or voucher schools, 33% and 53% respectively. When considering school quality, measure using tenth grade standardized test scores take in 2006, 52% of the students applying to college are in high-quality schools.[32]

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 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]

[31] In Chile the main region is the metropolitan region (RM), where Santiago, the capital of Chile is located. RM represents in 2014 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).

[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.

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 3). 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.

I present results for students by school and SES in Figures 7, 8, and C.3 considering overall rate of acceptance, acceptance rate in tier 1 and tier 2 colleges. Figure 7.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 7.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 8).

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 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 9 and 10 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 $s \neq e$.

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[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.

In Figure 9 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 10 that whenever the dispersion within school e's thresholds is lower than in school s, some students in both schools could benefit from switch 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 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

[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.

[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.

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.

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

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

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:

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

5.3.1 Equilibrium

A perfect-information competitive equilibrium is a tuple $\{q = (q_L, q_H), AS^*\}$ 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

[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.

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

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

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 9. Then using Constraint 1 and the fact that Equation 8 gives always a weakly higher application threshold for students in school L, $AS(gpa_i, L) \ge AS(gpa_i, H)$ 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 9, we have that students with a GPA between $gpa_L^* = AS_L^{-1}(AS_2^*)$, and $gpa_H^* = AS_H^{-1}(AS_2^*)$ switch schools. If this is the case, then the effect of policy on the number of students accepted in college from school L is reversed, and there is no change in the pool of students accepted into college.

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

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

5.4 Model's main predictions

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

First, only students in the middle of the school-specific GPA distribution have the 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.

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

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 11 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).

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 6 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 12 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

[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.

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 13 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 12. 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 14 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 14.a). When analysing the correlation between potential gain and realized 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

[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.

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.

[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.

7.3 Changes in the likelihood of switching schools for students in high quality 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 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 15 and 16 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

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

to have better socioeconomic background. In short, more advantaged students with parents with high aspirations are more likely to behave strategically in this context and switch schools during twelfth graede.

8 Discussion

Many affirmative actions for access to higher education have use schools to determine the targeted groups. This strategy seems obvious when we take in consideration the connection between the type (public, voucher and private) and quality of schools that students from historically disadvantage populations and communities attend.

An important problem with these type of *targeting* is the creation of incentives to game the policy for non-targeted students. Particularly, switching schools while in high school to be seen as part of the favored group.

In this paper I show that relocation of school is an important unintended consequence that has the potential to mitigate the expected effects of the policy. Further, using students' graduation school as the treatment when evaluating the policy might *help* to inflate the effects of the policy. Figure 17 shows the effect of the RR policy considering the school students started twelfth grade (first columns) and the school they graduated from high school. The effect of this policy is clearly misleading (and overestimated) if we consider the school students graduated.

9 Conclusion

This paper presents evidence that changes in college centralized admission systems can significantly incentive students' strategic behavior during high school, undermining the expected effects of the policy. Particularly, I show that students game an affirmative action that uses high school to increase chances of low socioeconomic students to attend college. I do so in the context of Chile. I evaluate the policy and estimate the effects of pre-college behavioral responses using a rich administrative records. The relocation of students had an effect on the policy effect, reducing its effectiveness by 90%.

The results suggest more privileged students are more likely to switch schools to gain points in their application scores, largley increasing the probability of attending a selective college. These results are consistent with results in the context of Texas Top-ten percent law (Cullen et al., 2013) and quotas in Brazil (Melo, 2021). Previous research has not being able to estimate the effect of strategic behavior in the policy expected effect. To alleviate concerns about the results being actually driven by changes in the educational system from previous and important reforms, 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 the clear rule change and detailed data.

Understanding the pre-college behavioral responses is key for effective policy design. Specially in times where unequal access to college is not longer a second-order problem for policy makers. The results of this paper suggest we should pay attention to high school students responses when designing college admission systems and policies. Finally, more research is needed to understand better how decisions in secondary education connects with students' value of tertiary education.

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Tables

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

	Centralized Admission		**Decentralized Admission**		
	Public Univ. (1)	Private U - Crunch (2)	Private U not-Crunch (3)	IP (4)	CFT (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 (1)	Fraction admitted (2)
Choice 1	1.000	0.444
Choice 2	0.926	0.194
Choice 3	0.813	0.117
Choice 4	0.592	0.069
Choice 5	0.418	0.050
Choice 6	0.285	0.039
Choice 7	0.197	0.029
Choice 8	0.137	0.021
Choice 9	0.092	0.013
Choice 10	0.064	0.013
Nb. students	119,161	95,568

Notes: This table reports 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.

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 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 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.

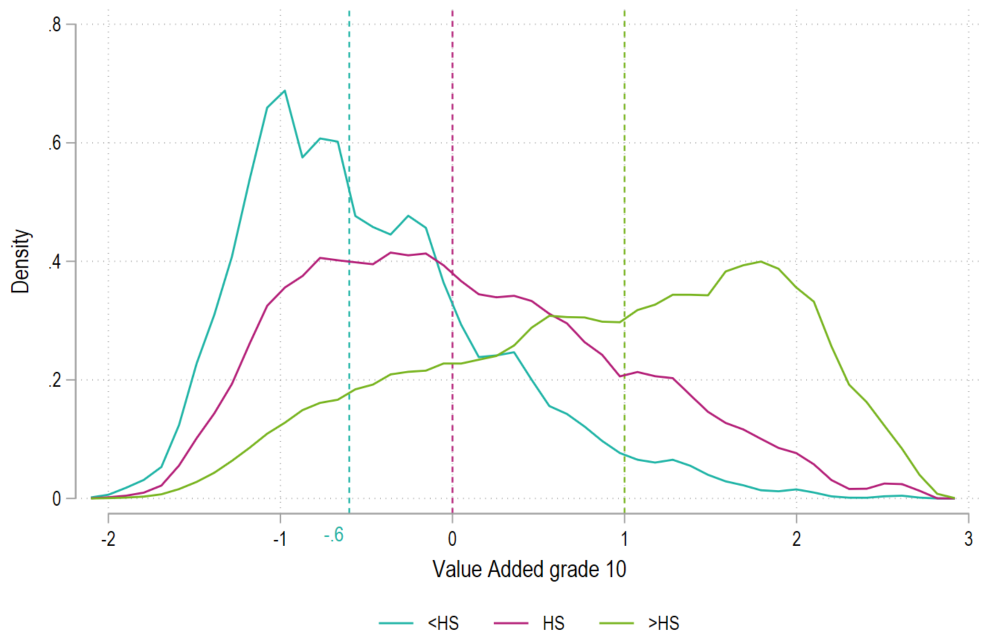
Table 7. **Difference in Difference estimation (2012-2014).**

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

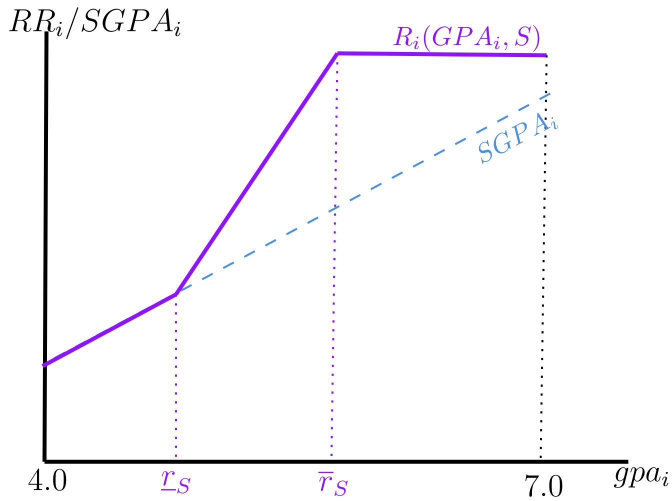
Figures

Figure 1. Inequality of School Quality Across Mothers' Education



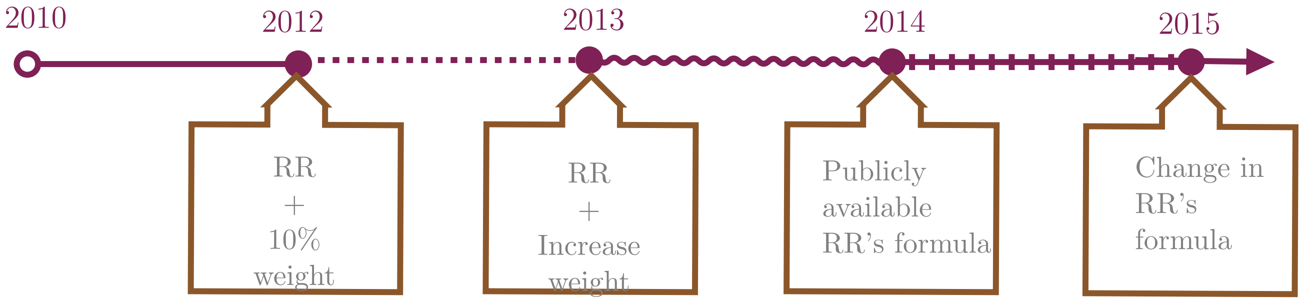
Notes: This figure depicts an histogram with mean quantitative test score for students in tenth grade in 2008 and at the end of high school by mothers education. Light blue represents students with mothers with less than high school level of education. Dark purple shows the distribution for students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

Figure 2. Relative ranking component visualization



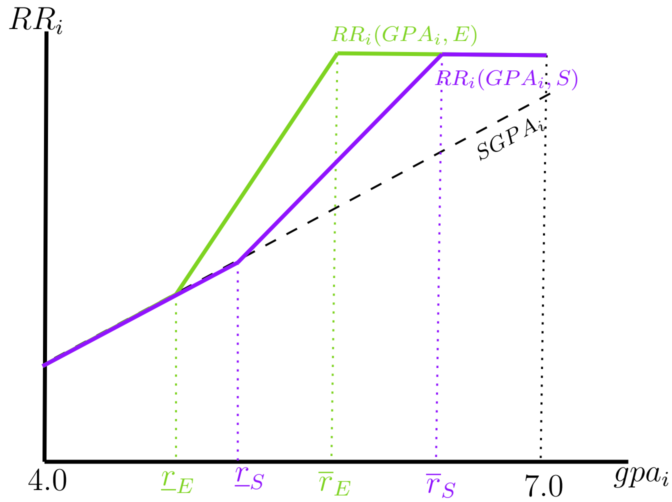
Notes: This graph depicts the formula used in Chile to create the relative ranking (RR). The blue dashed line shows the formula for student's standardized GPA (NEM) as a function of student's GPA. The purple solid line represent the non-linear formula to calculate the RR as a function of the GPA. $\underline{r}_S$ 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 3. Relative ranking policy's timeline



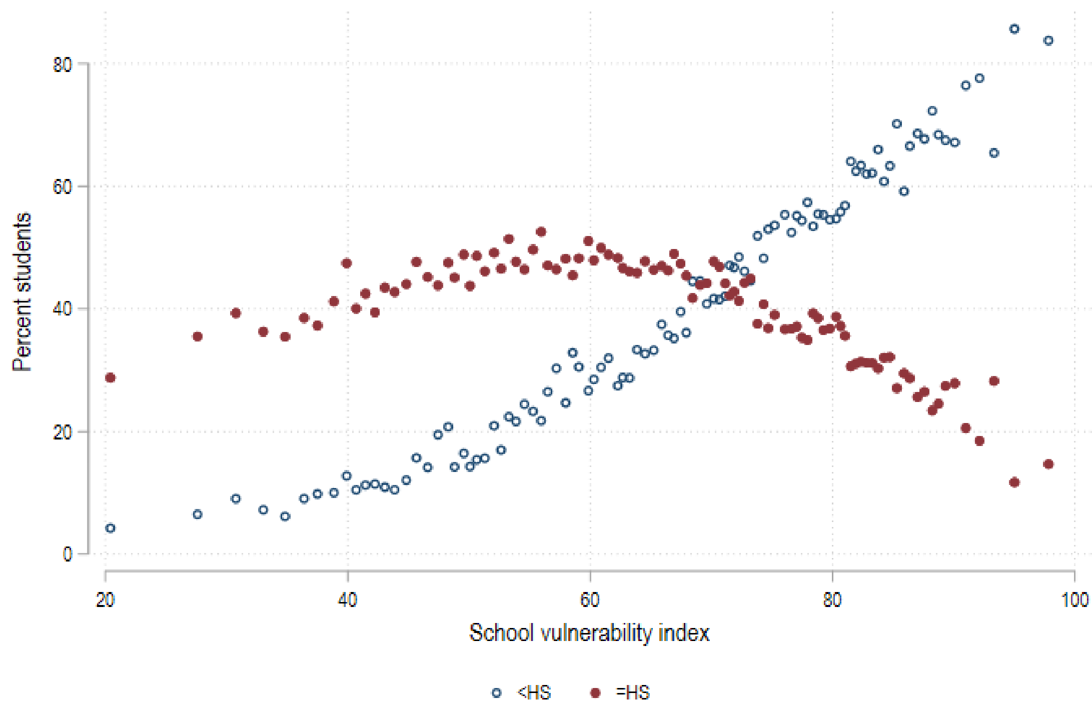
Notes: This timeline presents the changes made to the RR policy in different years. In 2012 they incorporated the policy with a weight of ten percent. This weight was subtracted from NEM's weight. In 2013 universities increased the weight associated to the RR. This new increase was coming either from 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 4. Relative ranking for two schools with different thresholds



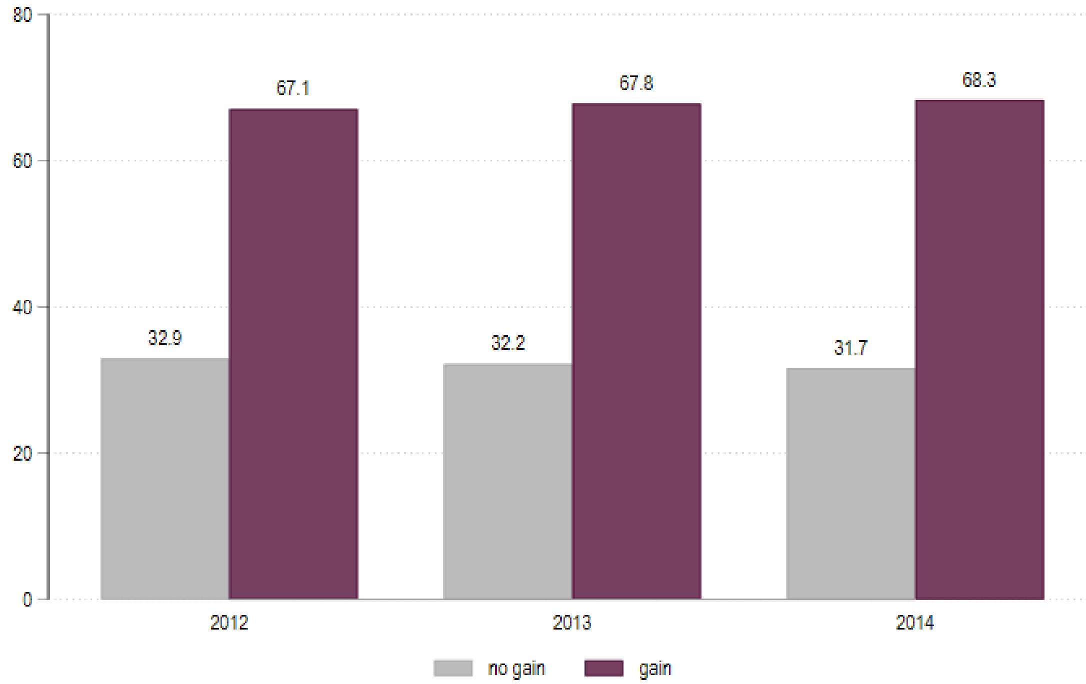
Notes: This graph depicts the formula used in Chile to create the relative ranking (RR) for two schools with different thresholds. The dark dashed line shows the formula for student's standardized GPA (NEM) as a function of student's GPA. The purple solid line represent the non-linear formula to calculate 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 5. 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.

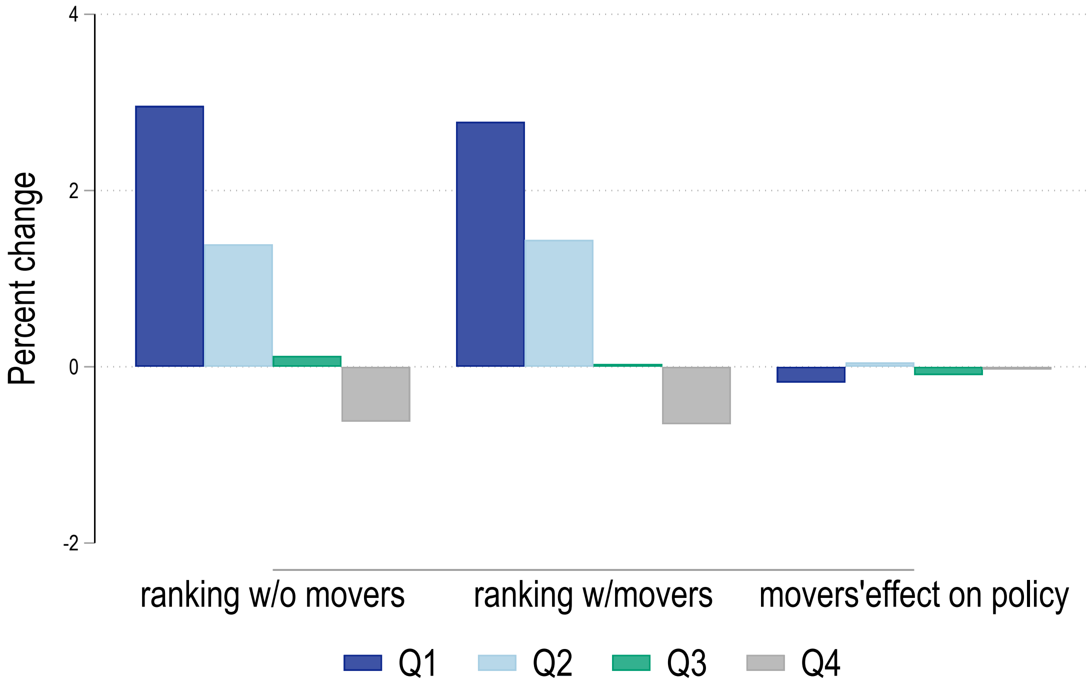
Figure 6. Ratio students with positive potential gain (2012-2014).



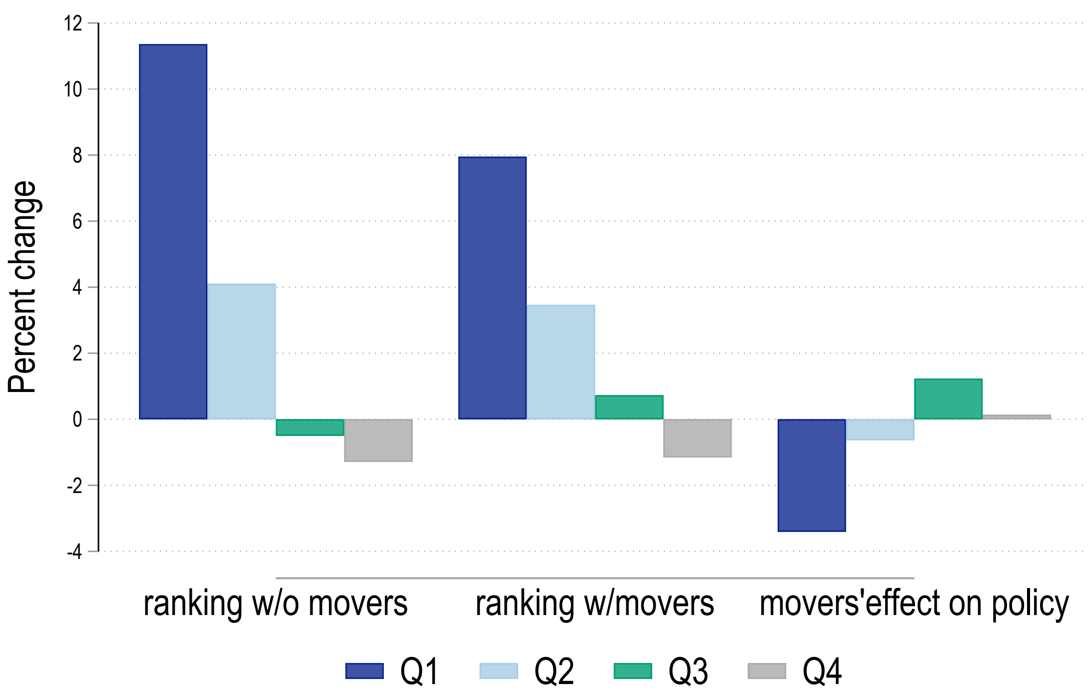
Notes: This figure presents the percent of students with positive potential gain (purple bar) and no potential gain (gray bar) in their choice set defined as an 4 kms buffer with the center in students' primary schools.

Figure 7. Policy effects in cohort applying to college in 2014 by schools' quality.

(a) Acceptance rate in *any* university



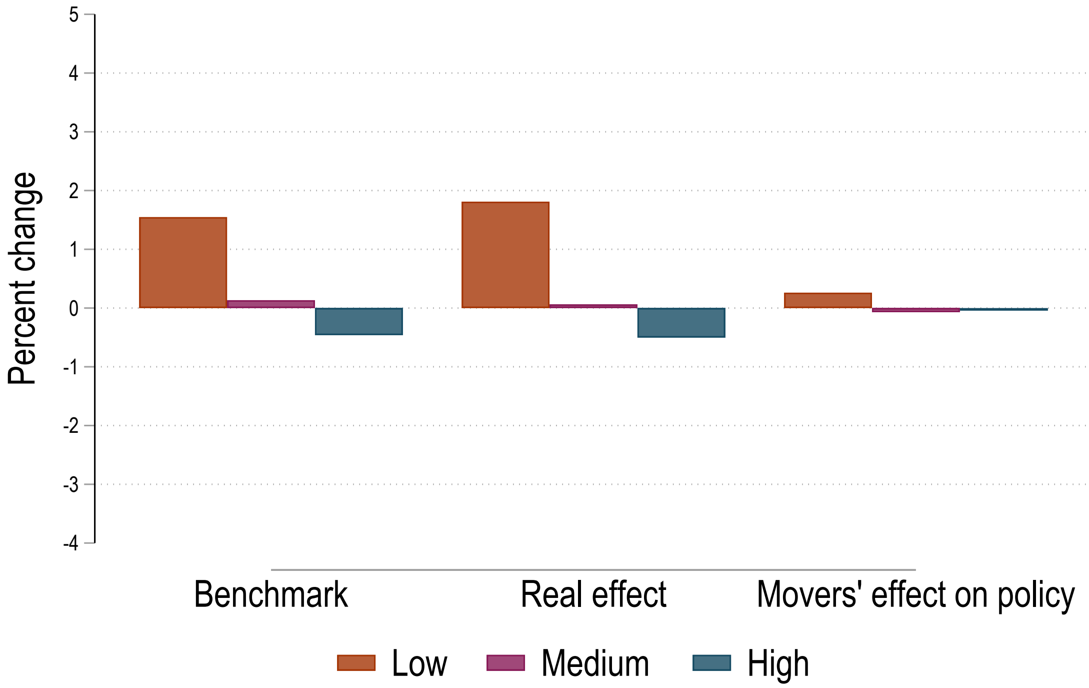
(b) Acceptance rate in *tier 1* universities



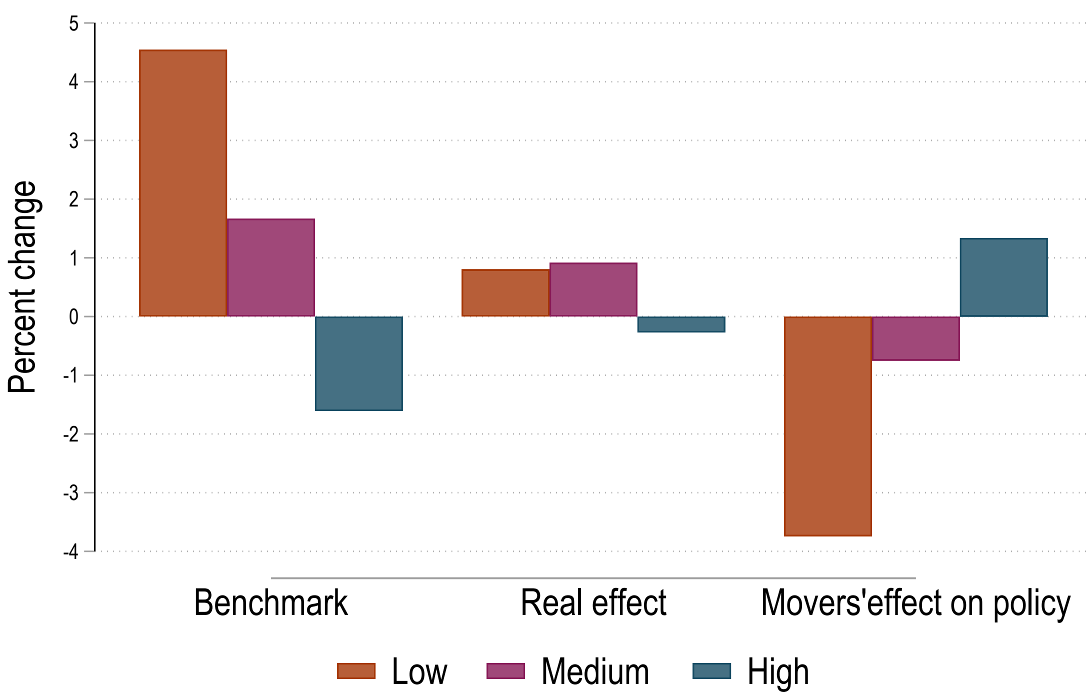
Notes: This figure depicts the percentage change in the number of students accepted in college by school's quality. Denominator in the percentage is the number of students accepted into each category without the policy. Figure (a) presents the changes in rate of acceptance in any university. Figure (b)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

Figure 8. 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 9. Same thresholds' order

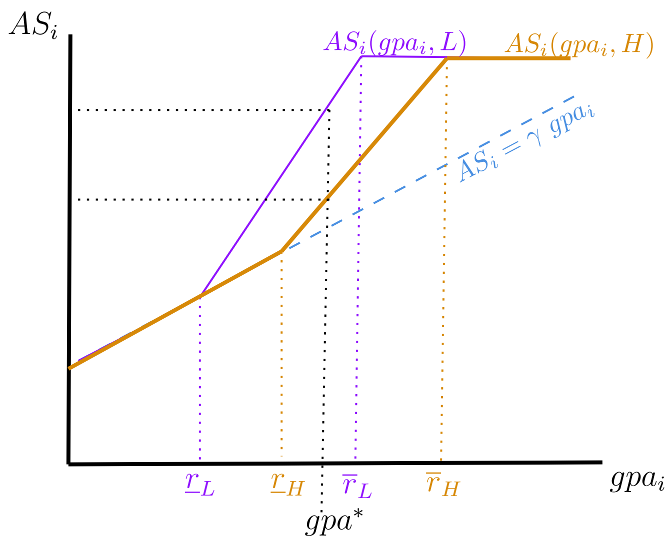


Figure 10. Different thresholds' dispersion

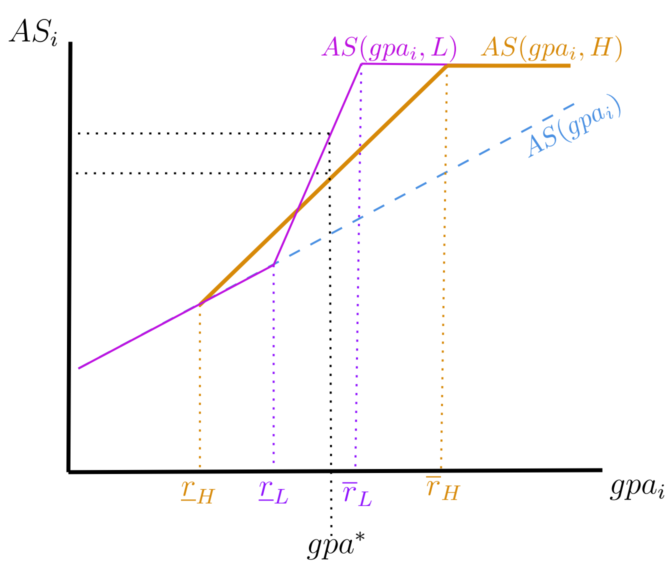
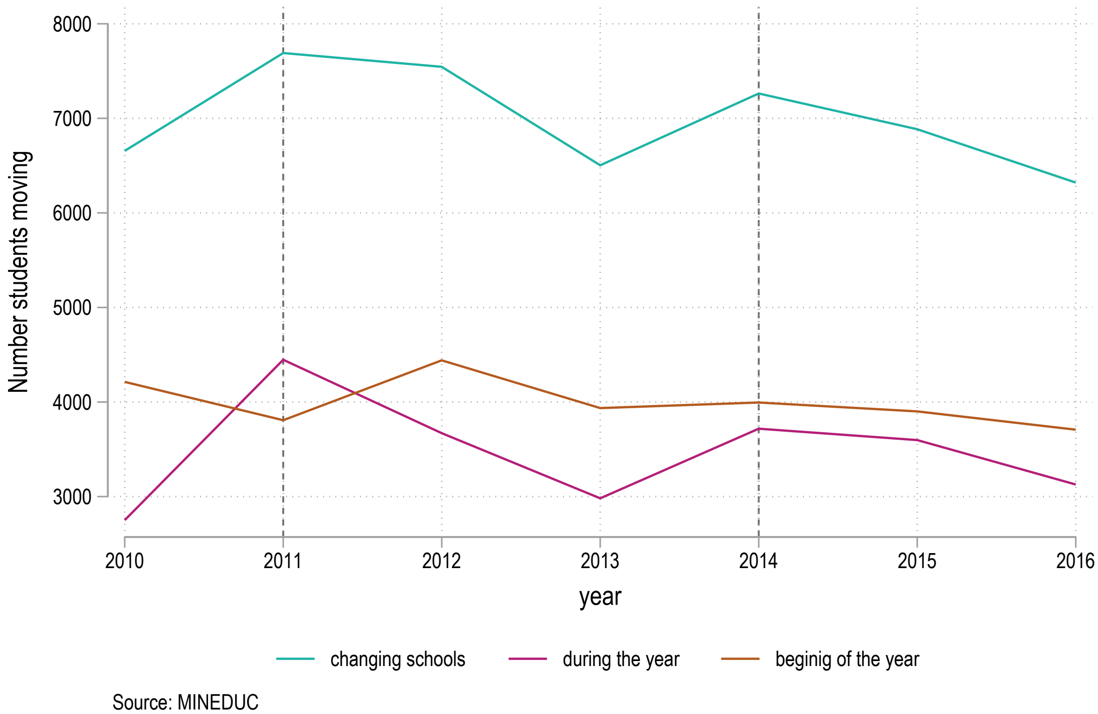
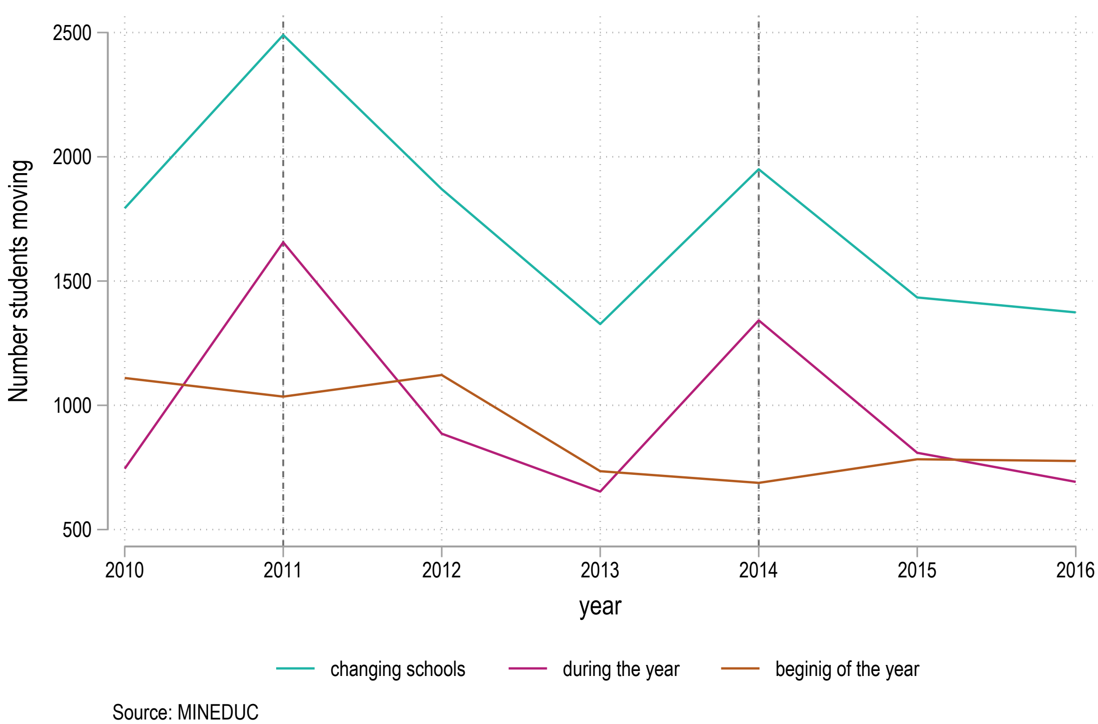


Figure 11. Number of students switching schools in twelfth grade (2010-2016)

(a) *All* students



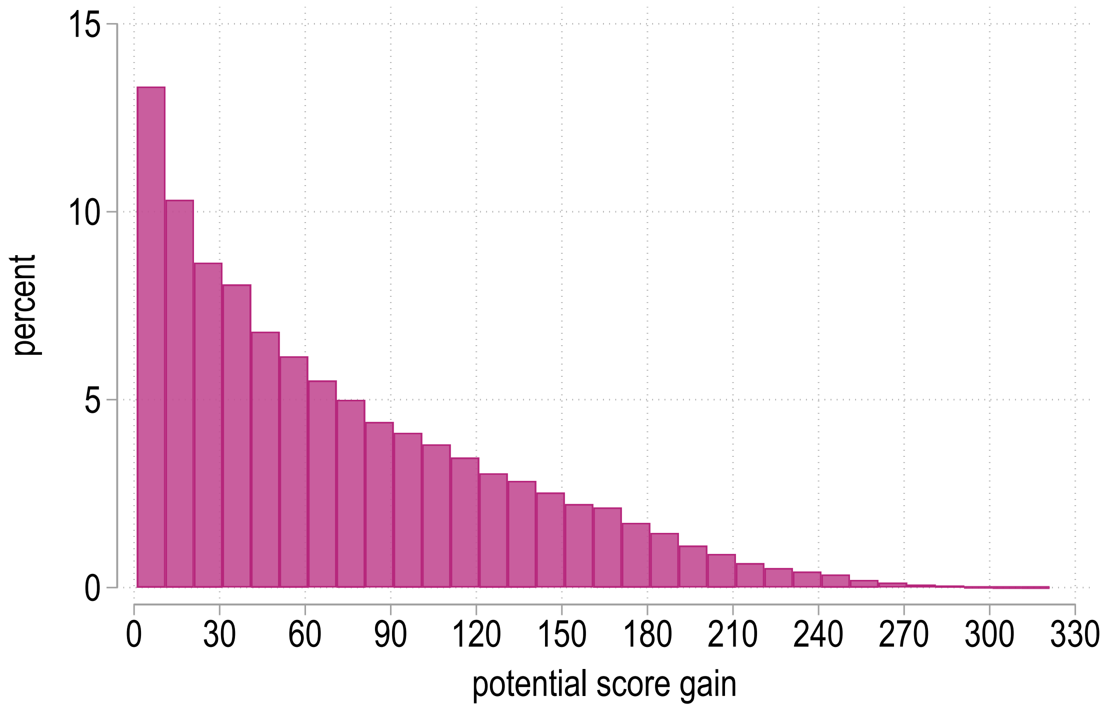
(b) Students in *top* schools



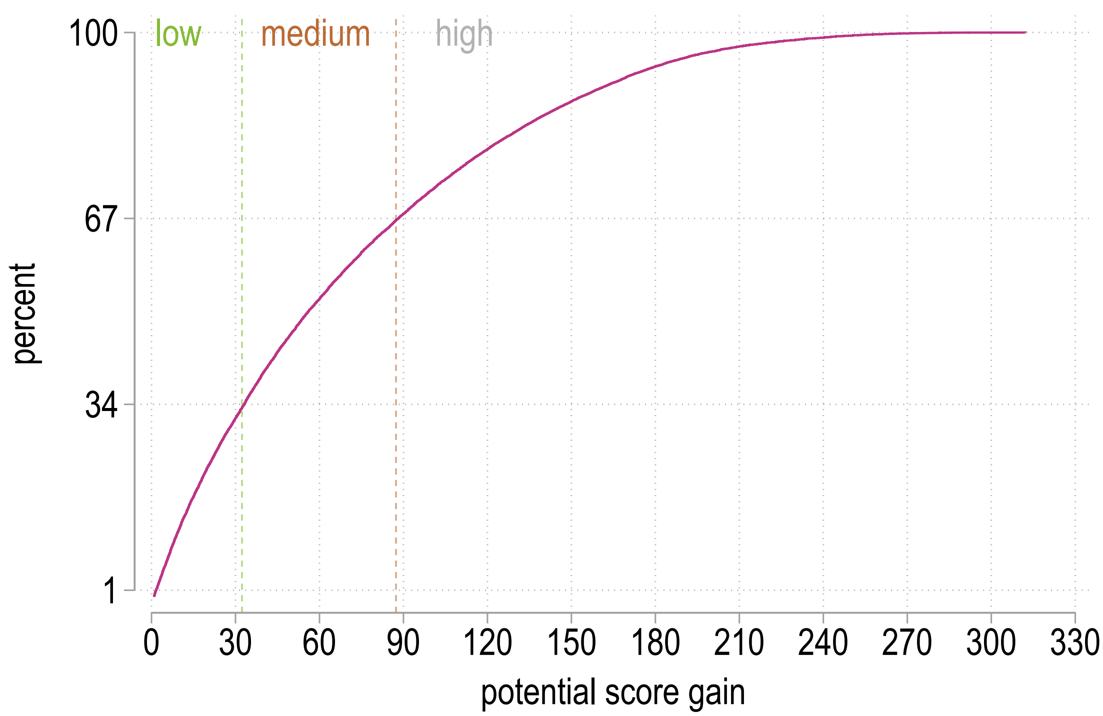
Notes:

Figure 12. Potential score gain, 4 km buffer (2014)

(a) Distribution

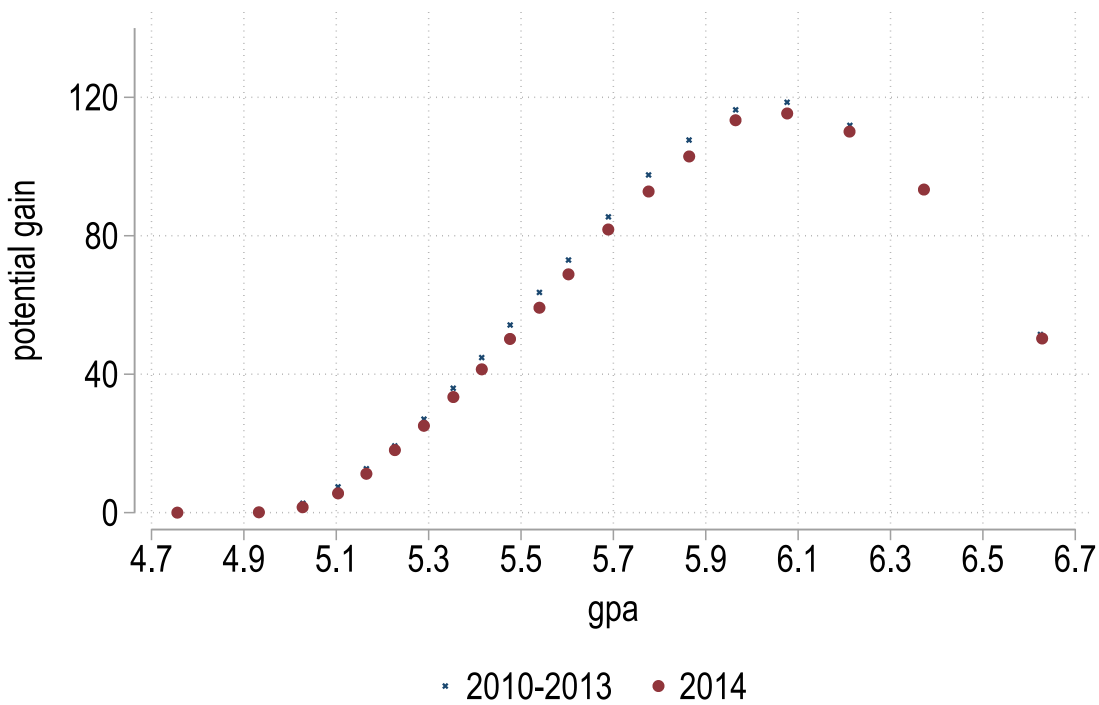


(b) Empirical distribution



Notes:

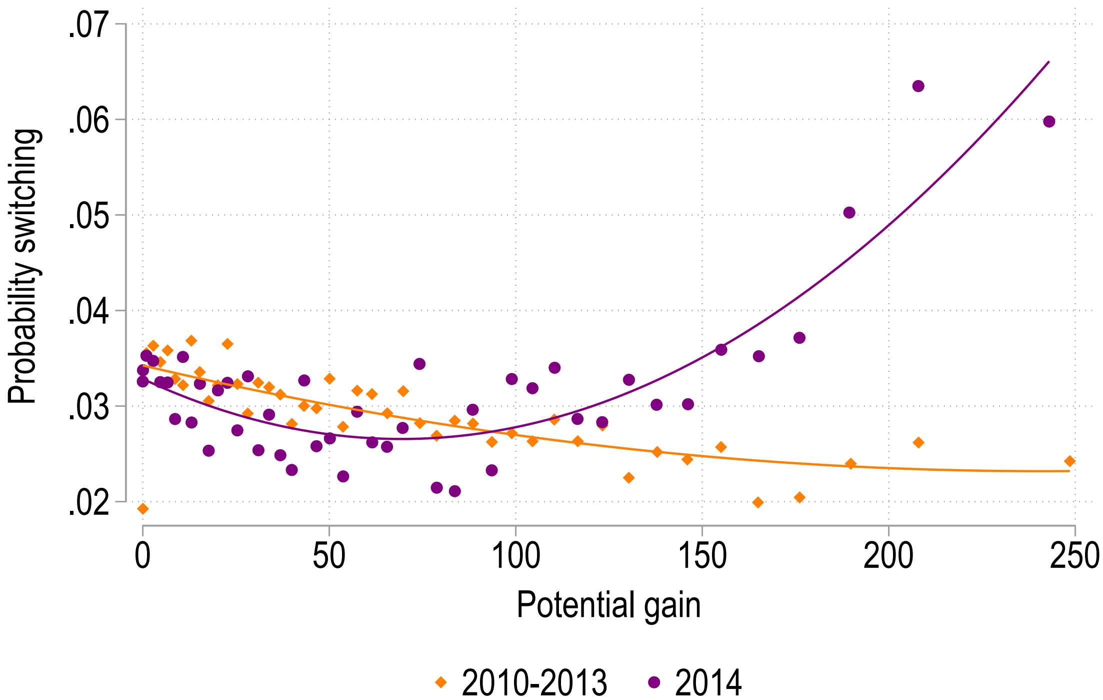
Figure 13. Potential score gain and GPA, 4 km buffer (2010-2014)



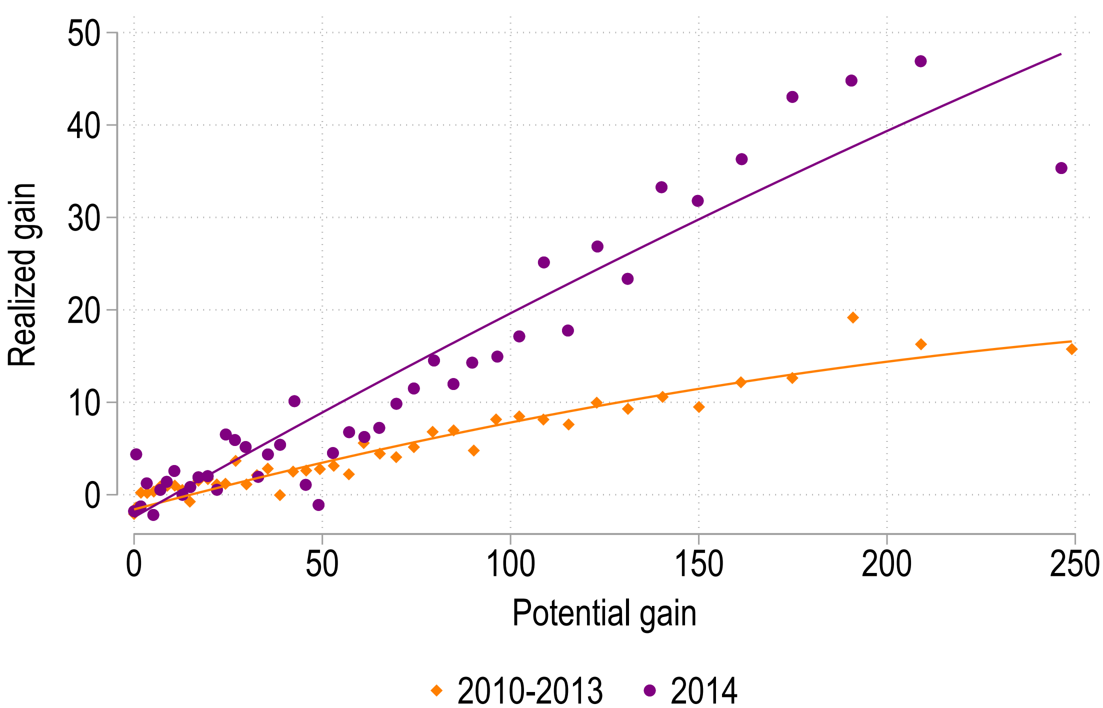
Notes:

Figure 14. Potential score gain, realized score gain and probability of switching (2010-2014).

(a) Potential score gain and probability of switching schools

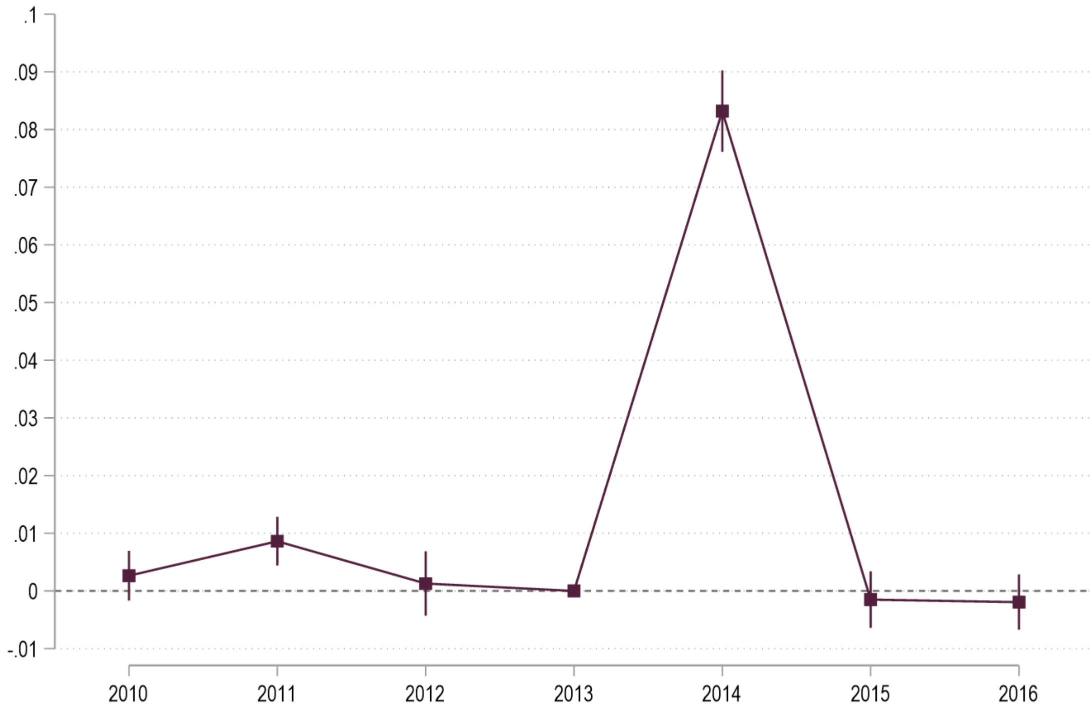


(b) Potential score and realized gain



Notes:

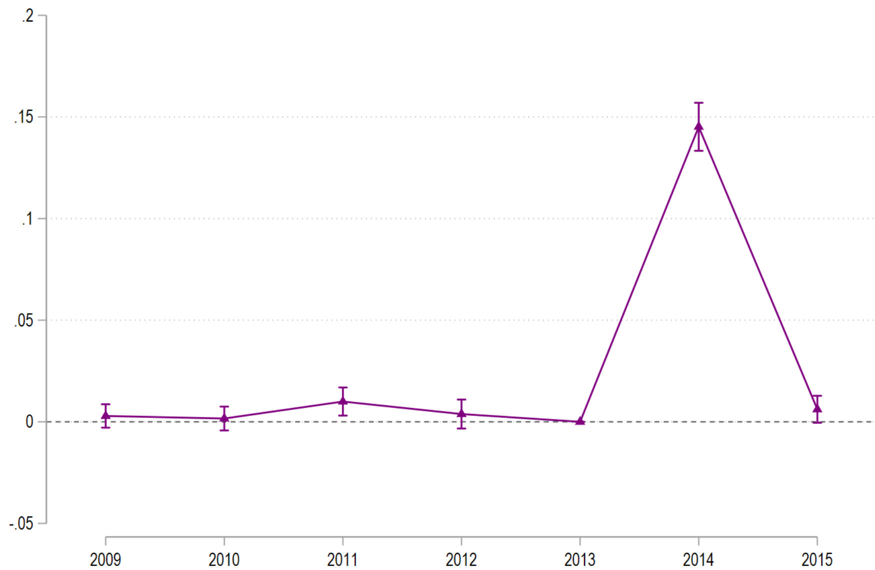
Figure 15. **Probability of switching schools.**



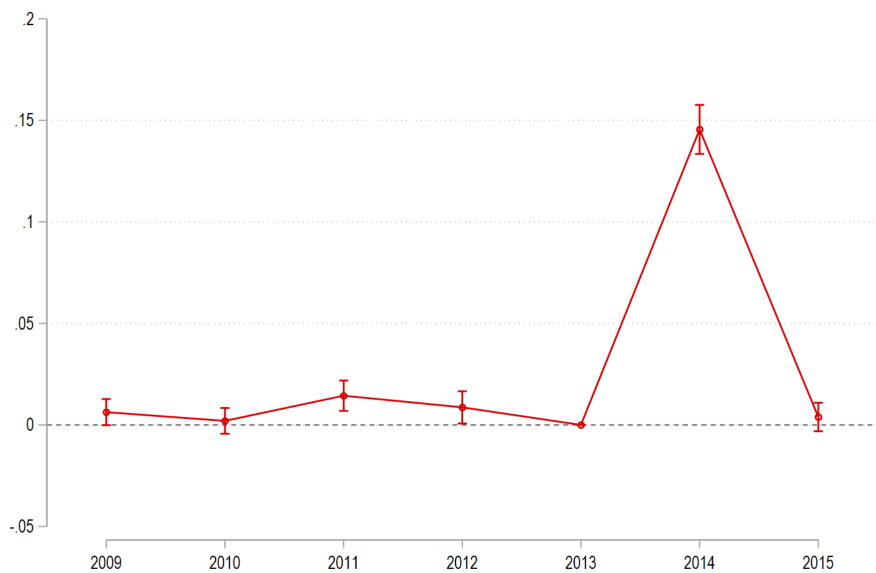
Notes: This figure depicts an event study design for probability of switching school. The coefficient represents the difference in each year in the unconditional probability of switching school for students in elite and non-elite public school in the metropolitan area. *Data sources*: Chilean Minister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

Figure 16. **Strategic switching**

(a) Targeting lower mean thresholds' schools

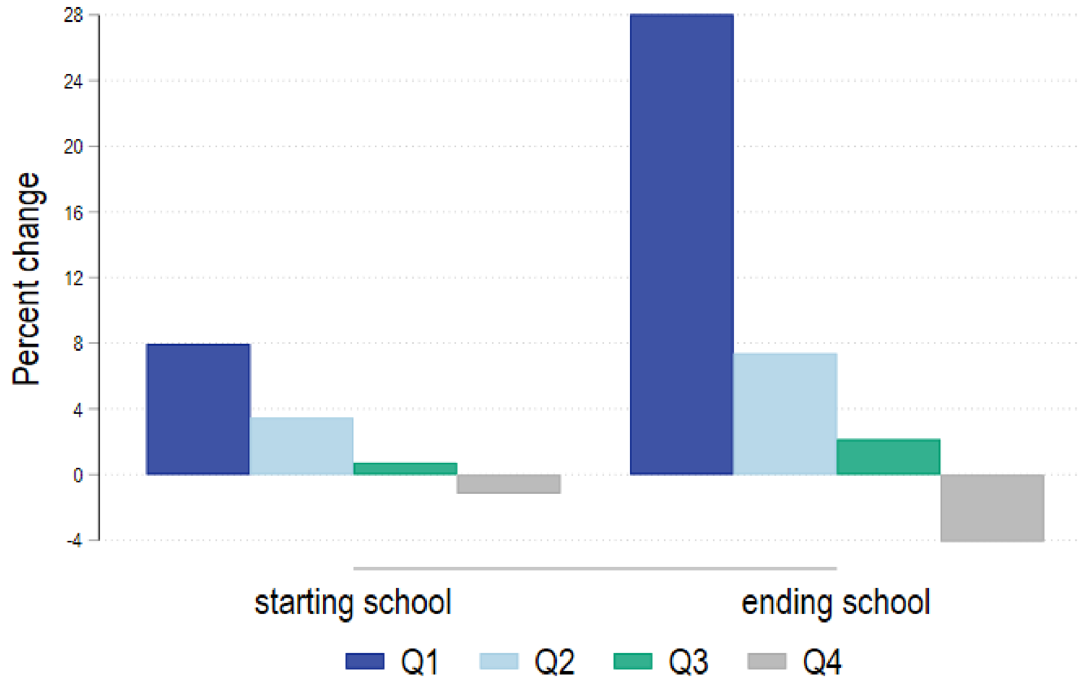


(b) Targeting schools who sent less number of students to college pre-policy



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 17. **Probability of switching schools.**



Notes: .

Online Appendix for:

Should I Stay, or Should I go? Strategic Responses to Affirmative Action Policies in Centralized College Admission

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. $\square$

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 10). 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.

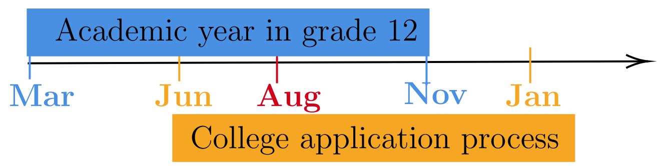
Finally, suppose a fraction q of students with a potential gain in switching, have a cost of switching higher than the value of college. Then only that fraction of students switch schools, and therefore the pool of accepted students into college change in a ratio equal to $1 - q$.

□

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

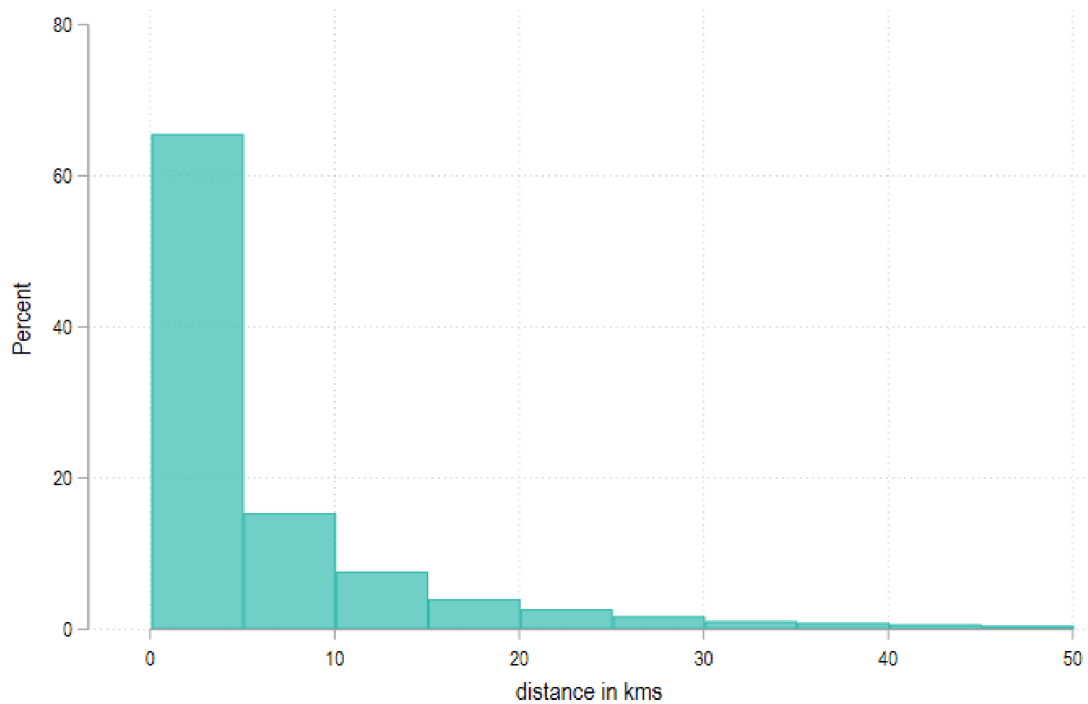
C Additional tables and figures

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).

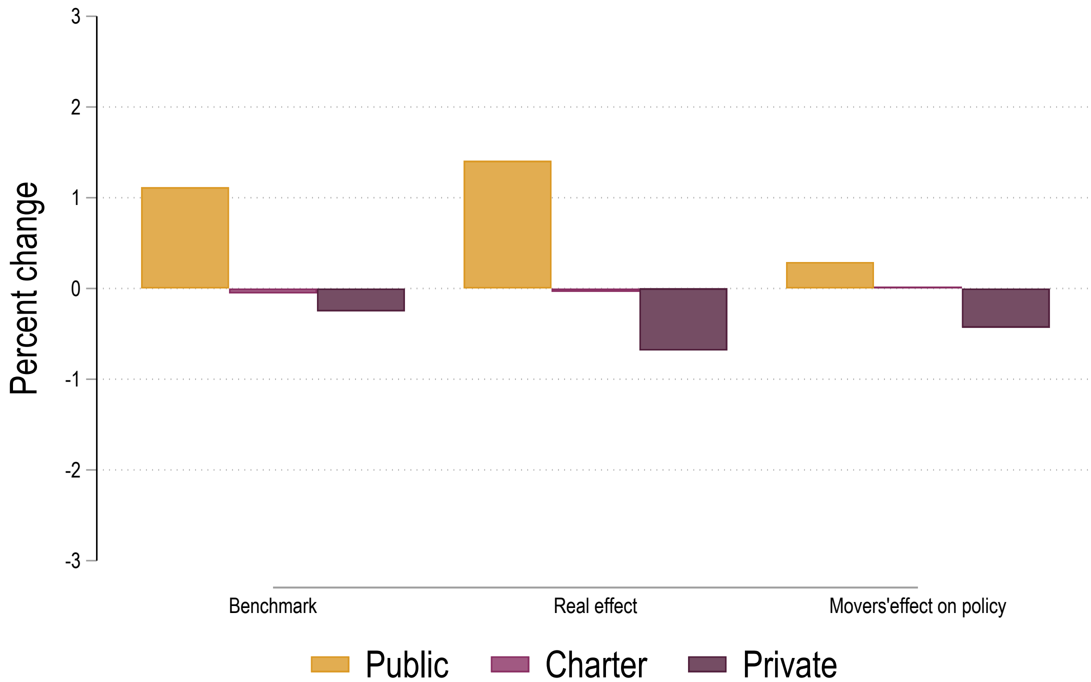
Figure C.2. Distance in kilometers between student's primary and secondary school (2014).



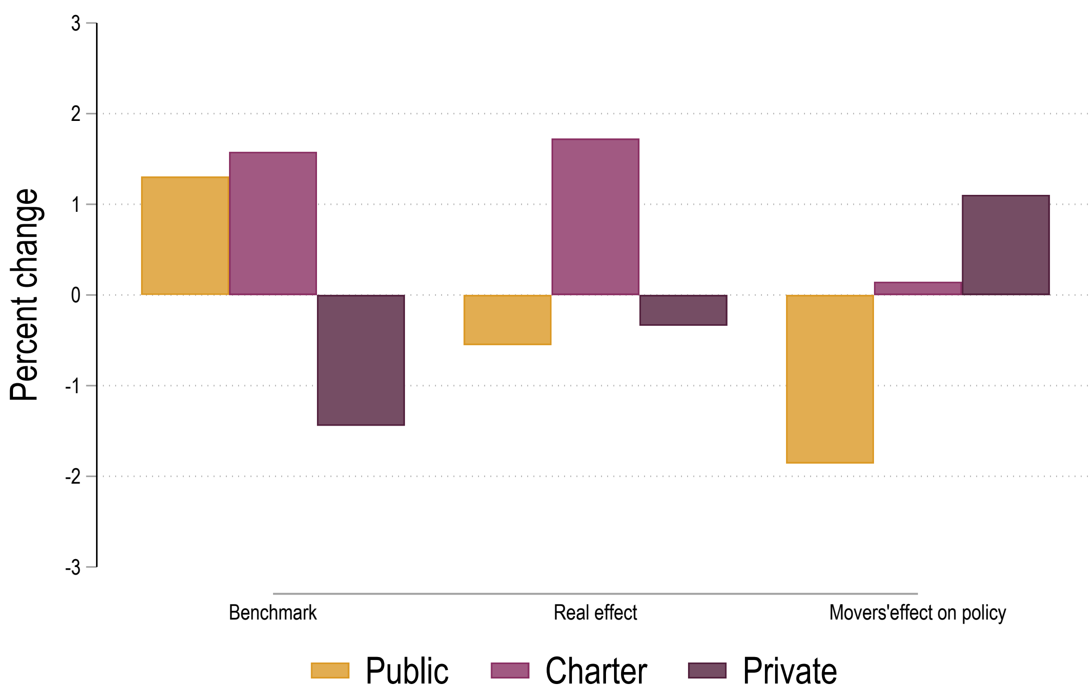
Notes: This figure presents the distribution of real distance in kilometers for students' initial school in grade twelfth with respect to their primary schools. I exclude here students who are in the same school than primary school since the distance in that case is zero. More than seventy percent of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



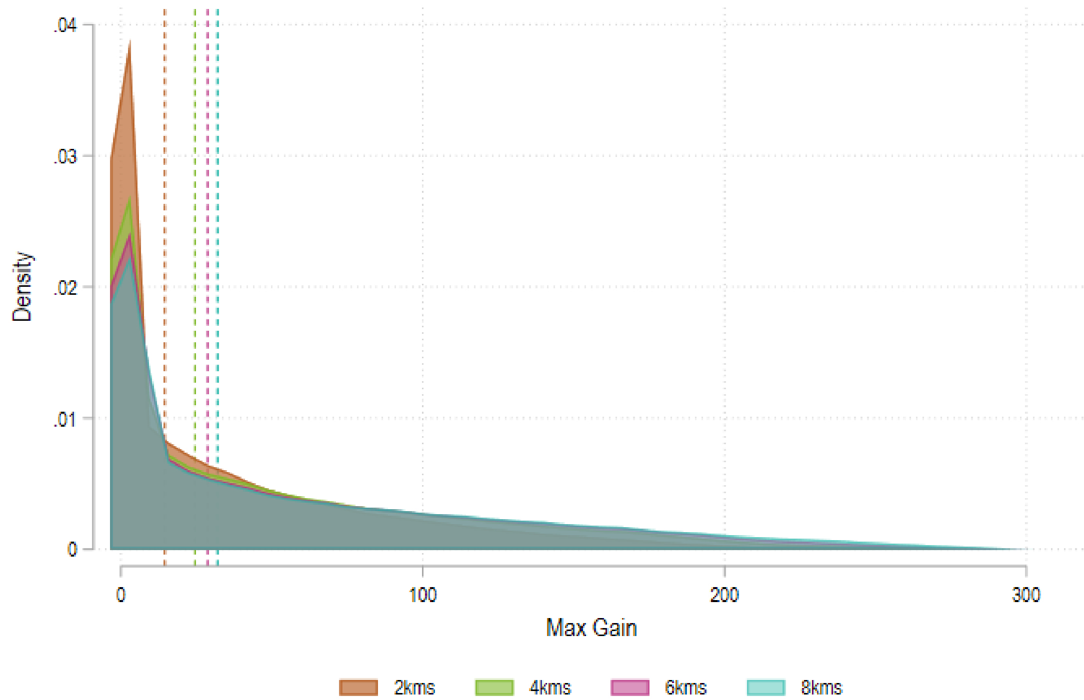
(b) Acceptance rate in *tier 1* universities



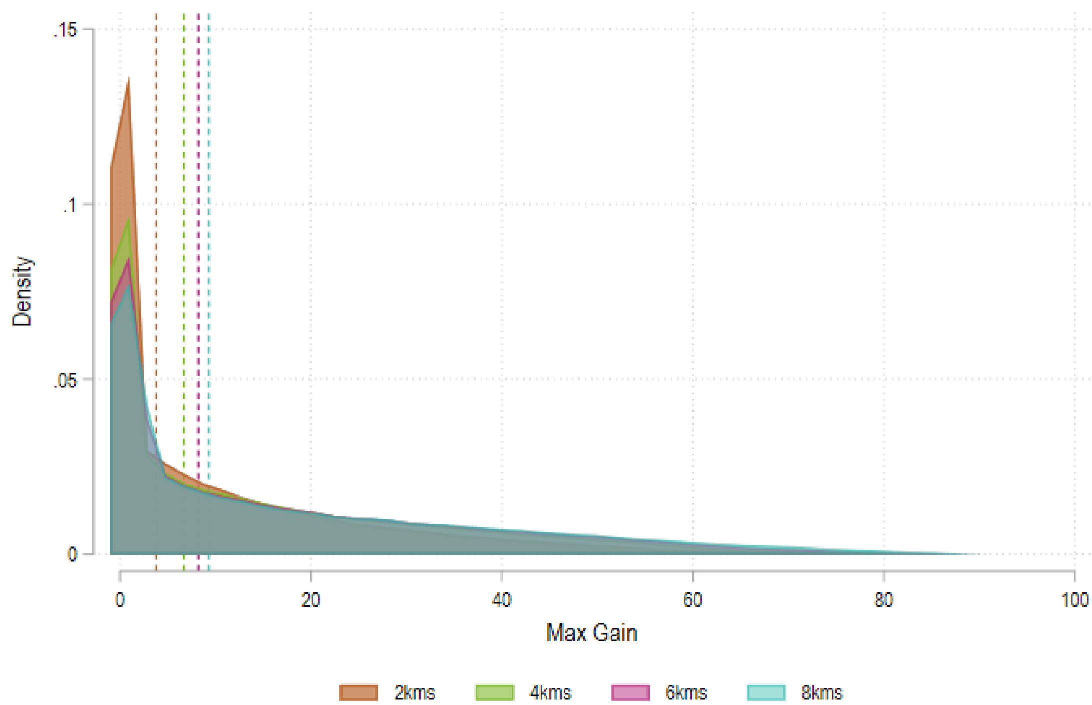
Notes: This figure depicts the percentage change in the number of students accepted in college by type of school. Denominator in the percentage is the number of students accepted into each category without the policy. Figure (a) presents the changes in rate of acceptance in any university. Figure (b)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

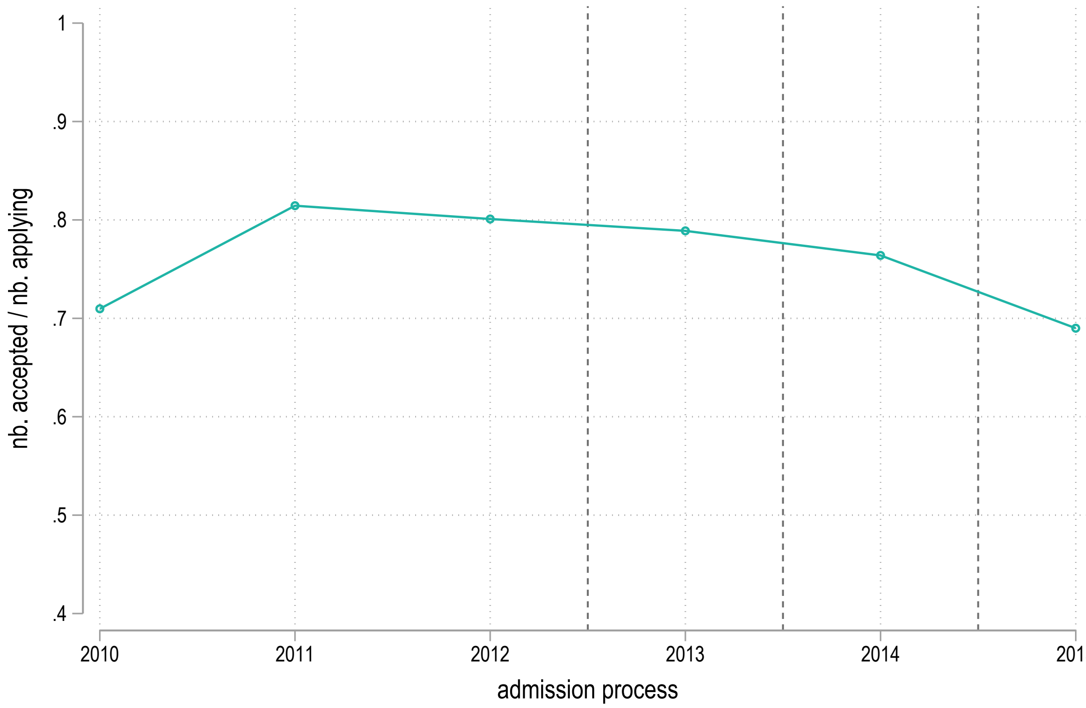


Notes:

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

Notes:

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



Notes: