College admissions with a local context GPA: Giving good students better college options

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October 30, 2022

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Abstract

Many college admissions systems use a combination of GPA and standardized test scores to determine access to more selective programs. In this paper, I study the impacts of a 2013 reform of the Chilean selective college admission system that introduced a third component, based on a student's relative GPA, designed to improve equity in the system. Simulating the admission mechanism with and without the relative GPA boost, I classify 2013 applicants into three groups: (i) those who gained access to more selective programs (pulled-up), (ii) those who lost access to more selective programs (pushed-down), and (iii) those whose admission was unaffected. Simulating the admission mechanism in earlier years with and without the same boost, I identify the groups who would have been pulled-up and pushed-down in those years, facilitating a difference-in-differences design to estimate the impacts of the relative GPA boost on enrollment, graduation, and earnings of winners and losers from the reform. As a result of the reform, pulled-up students shifted to programs with higher-performing peers and higher graduation rates, and experienced a large increase in the probability of graduating from a selective college program over the next 8 years, though no gain in BA completion. Pushed-down students, who tended to come from better-educated and higher-income families, experienced comparable-sized reductions in the probability of graduating from selective programs, offset by gains in graduation from less selective programs. My findings suggest that a targeted boost in admissions rankings based on relative GPAs can enhance the equity of a selective admission system without incurring large efficiency penalties.

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Introduction

The notion of education, especially high return degrees, as a vehicle for upward social mobility makes the topic of how students access different universities policy relevant (Autor, 2014; Chetty et al., 2017; Turner, 2020). Admissions policies at selective colleges tend to primarily rely on standardized test scores, but the consistent evidence of disparities in test scores between student from different backgrounds has sparked a policy discussion regarding equity issues (J. M. Rothstein, 2004; Card & Rothstein, 2007; Zwick & Greif Green, 2007). Interventions in the admissions process, such as affirmative action and top-percent policies in the United States, are instances of this effort to close the observed admissions equity gap.[1] However, the undetermined effect of admission interventions on retention, graduation, and earnings has raised worries about a potential conflict between equity in admission and its impact on the efficiency of the higher education system.[2]

Estimating the causal effect of any intervention is difficult, but even more so when it is difficult to identify the treatment groups. In the setting of selective colleges and fixed capacity, equity admission interventions are subject to an intrinsic trade-off: when one group's admission is made more competitive, another group's admission becomes less competitive in comparison. Identification of the second group is typically more difficult due to the need for specific understanding of the admissions requirements at selective institutions. Moreover, in order to evaluate the (outcome) efficiency impact of an admission intervention, the typical challenges of estimating the causal effect on a single group are still present: a sound empirical design and data availability in relevant outcomes, among others.

This paper extends the knowledge around the effect of admission to selective colleges and access-oriented admission interventions by studying not only the direct effects but also

[1]For California's "Eligibility in the Local Context" see Bleemer (2021),and Black et al. (2020) for Texas Top Percent Policy. For Brazil's affirmative action Otero et al. (2021) and Mello (2022) and Bagde et al. (2016) study an affirmative action policy in India

[2]Dillon & Smith (2020) highlight this potential trade-off between equity and efficiency. In the case of California, Arcidiacono & Lovenheim (2016) find mixed evidence on the benefit of admission trough affirmative action. On the other hand Bleemer (2021) presents evidences that support that the benefit of more selective university enrollment is greater for affirmative action's under represented minorities enrollees

the indirect effects on the entire college system. In order to do it, I exploit a unique and comprehensive equity reform in the Chilean college admission system that incorporates a local context GPA measure (GPA$^+$) into the application process. The purpose of the reform was to adjust admissions with a measure that took into account between-school disadvantages and allowed "good" students with fewer educational opportunities in the past to be more competitive in college application. The new measure is a score based on the high school GPA score of the student adjusted by a boost when students perform above the historic average of students of their same high school, therefore the local context name. The introduction of the new measure created implicitly three groups of students: (1) students that got access to better admissions (pulled-up), (2) students that got access to worse admissions (pushed-down), and (3) students that didn't have their admissions affected. I conduct a comprehensive analysis to identify and characterize the two groups of treated students. Additionally, I estimate the effect of the reform in terms of human capital acquisition and labor market outcomes in order to account for the allocative efficiency impact in aggregate terms.

I find that the reform gave access to more selective college options to students from lower income and less educated families, but with good relative performance in high school. Getting access to these programs made pulled-up students more likely to enroll in a selective college, and made them more likely to attend programs where their classmates had higher test score and higher GPA in high school, as well has higher probability of graduating on time. Contrary to the mismatch hypothesis (Sowell, 1972), that established that low-test students targeted by access-oriented admission programs, like affirmative action, would be better off by attending programs where they match their peer characteristics, I find that the probability of graduation from the more selective program increases by 8 p.p. and preliminary results suggest that earnings increase. For pushed-down students, probability of enrollment in selective college options decreases, but there is no change in the probability of college attendance due to the increase in non-selective enrollment and the increase of enrollment in the selective system after the first year. Overall, the evidence confirms that the inclusion of the local context GPA measure to the college admission process increases admission equity without an efficiency loss.

Specifically, I exploit the variation generated by the local context GPA reform to identify the effects of access to better college options to students who didn't have those options in the past. Contrary to most papers that look at only one margin of selectivity, I look at the effects in the entire system, where a more selective program means that students are required better academic performance to be admitted than in a less selective program.[3] Additionally, I assess the indirect effect of losing access to better college options by estimating the effect on students who, as a consequence of the admission reform, were displaced from their college options in the selective system. Finally, the availability of the data allows me to track students through the entire college system (including the non-selective universities) to understand the ways that students respond to admission changes.

I use the rich information on preferences contained in students' rank order lists and the transparency of the college admission rules to simulate students' assignment under the two admission regimes: status quo (SQ), pre-reform, and GPA$^+$, post-reform. The Chilean college admission system is a centralized system that used a Deferred Acceptance (DA) algorithm to match students to programs.[4] By replicating the mechanism, I simulate the counterfactual admission assignment that students would have gotten under the two regimes. This allows me to identify the set of students that could gain access to a better program with the reform - pulled-up - and those who could lose access to the programs that they used to access - pushed-down.

To estimate the causal effect of the reform on pulled-up and pushed-down students, I use a difference-in-differences design for outcomes on human capital acquisition and labor market outcomes. Simulating the admission mechanisms in earlier years, before the

[3]Black et al. (2020) look at enrollment in UT Austin with the implementation of Texas Ten Percent policy and Bleemer (2021) analyse the University of California system with the implementation of Eligibility in the Local Context.

[4]Admission is offered only to the most preferred program reported by the student for which they are eligible for based on their admission test scores and GPA. In each admission process enrollment can only occur at the admission program, even if the student is eligible for other less selective options listed as less preferred. Other centralized college admission system that use a similar system to match students to programs are Norway, Denmark and Turkey.

implementation of the reform, I can identify the students who would have been pulled-up or pushed-down in those years. The difference-in-difference approach compares students in the same treatment group, before and after the reform was implemented. In order to control for time changes I use the information from students unaffected by the reform. The variation induced in the outcomes of interest by the implementation of the reform is unrelated to unobservable characteristics that also determine the outcomes, allowing for a causal interpretation of the effect of giving access to more selective programs.

The primary identification assumption is that in the absence of the reform, the trend in the outcomes of interest for pulled-up, pushed-down, and unaffected groups would have evolved similarly - also known as parallel trends. In order to check this assumption, I conduct a placebo exercise; following the same strategy to classify students into the three relevant groups I use the same diff-in-diff specification for cohorts for which no reform was implemented (2011 and 2012). I find no significant difference between them when no reform is implemented. For the identification of the treatment groups the main assumption is that the rank order list reported by students doesn't change with the incorporation of the local context GPA measure in the application score. Without restrictions in the report of preferences, the dominant strategy for the DA algorithm is to report preferences truthfully (Gale & Shapley, 1962; Roth, 1982). I assume that student preferences over programs don't depend on the inputs used by the assignment mechanism (test scores, GPA and GPA^{+}), and I use the fact that most students' list fewer than the maximum number of choices (Haeringer & Klijn, 2009; Pathak & Sönmez, 2013) in order to support the use of the reported rank order list to estimate the counterfactual assignment. However, a more recent literature has suggested a reporting behavior dependant on the feasibility of the options (Fack et al., 2019; Larroucau & Rios, 2018). Because the introduction of the boost could have changed those options for student with a high boost I test the sensibility of my results to samples without extreme boost values and alternative assumptions for inference; I find the same qualitative and quantitative results.

As a validation exercise, I use an alternative research design to examine the impact of getting access to the most desired program in a cross-sectional setting pre implementation of the reform. Using a regression discontinuity design, an estimating approach that relies on local randomization around the admission cutoff, I am able to compare the magnitudes of my estimates within the same context. Even though the RD design identify the effect of gaining access to the most preferred program for the marginal student, which could differ from the pulled-up group of students, I find that the enrollment and program completion effect estimates, considering the relevant margins of treatment, are in the same order of magnitude than the effects estimated with the diff-in-diff design for the pulled-up group (in the entire distribution and not only at the margin). Students that gain access to their most preferred option are are 16 p.p. more likely to enroll and 6 p.p. more likely to graduate from the program.

My results also align with the results from other equity admission interventions that find that access-oriented admission policies at selective universities can promote economic mobility without efficiency losses (Otero et al., 2021; Bleemer, 2021; Black et al., 2020). Consistently with the results reported in Black et al. (2020) for the Texas Top Percent policy, I find similar graduation rates (inferred) for pulled-up students than for the average students pre-reform, suggesting that pulled-up students didn't struggle more.

This paper contributes to the understanding of equity admission interventions and the effect of admission to more selective universities for students who would not normally have access to them by including the effect in the entire population of applicants, i.e. effects on pushed-down students, and by examining the effect on the entire college system (selective and non-selective institutions). I build on prior empirical research employing a difference-in-differences approach, and take advantage of the transparency of the admission criteria in order to precisely identify the treatment groups resulting from the admission reform. Unlike earlier studies, this admissions change affected the full spectrum of selective colleges, not just the access to a single institution. I contribute to the literature on the mismatch hypothesis by providing additional evidence against it in an environment that stands out as suited for evaluating it.[5]

[5] This literature focus on the potential negative effects of college selectivity on students admitted trough alternative mechanisms to academic performance. Several papers study the mismatch hypothesis with varying results, see for example Sander & Taylor (2012); Arcidiacono & Lovenheim (2016); J. Rothstein & Yoon (2008); Bleemer (2022); Arcidiacono et al. (2011)

The rest of the paper is organized as follows. In Section **??** I discuss the literature more related to this paper; Section 1 outline the features of the Chilean setting, the policy and the data sources; Section 2 present the empirical strategy, which is divided into two subsections: (1) the identification of the treatment groups, and then, (2) the discussion of the difference-in-differences design to estimate the treatment effect of the reform on those groups. Section 3 present the results for enrollment, graduation and earnings; the effects of the reform on STEM applicants and the evaluation of the mismatch hypothesis are also discussed in this section, as well as a series of robustness checks. Section 4 presents an alternative design to validate the results presented in Section 3, and Section 5 concludes.

1 Context

The Chilean test-based meritocratic college admission system is an ideal setting to evaluate the effects of an access-oriented admission intervention like the 2013 reform. It introduced a new component (the local context GPA measure), based on the student's relative GPA, designed to improve equity in the system. The transparency of the system, together with the availability of rich administrative data allows for the simulation of admission offers with and without the new GPA$^+$ component even in years before the reform was implemented, facilitating the construction of meaningful counterfactuals for winners and losers of the reform.

1.1 Chilean College Admission System

The admission process to selective universities in Chile is a centralized score-based meritocracy, based solely on standardized admission test scores and the high school GPA score of the students. The assignment mechanism - that uses a deferred acceptance (DA) algorithm- generates a seemingly strategy-proof environment and can be replicated when admission preferences, program vacancies and applications scores are available. I discuss with detail this two key characteristics to the implementation of my empirical strategy, particularly to the identification of the two treatment groups.

The college system and application procedure The Chilean college system has selective (public and private) and non-selective (private) colleges.[6] To enroll in a selective university students have to (i) graduate from high school, (ii) take the standardized admission test at the end of the academic year, and (iii) submit a rank ordered list of their preferences to the centralized admission system after learning about their test results. This process happens once-a-year and students can enroll only if they get an admission offer. To enroll in a non-selective college, students have to apply directly and follow the requirements of each institution.

An important difference from other college systems is that it is organized around programs, instead of majors and universities. Programs have a highly fixed curriculum (which makes switching programs hard and not common) with expected times for graduation between 4 to 7 years (5 being the mode). In most programs, students earn an academic degree after 4 years but they are required to attend a 5th year and pass a licensing exam to earn their professional degree and complete graduation. Programs provide the complete certification for most occupations, such as architecture, law, or medicine. This characteristic of the Chilean college system makes the relationship between college and labor market outcomes tighter compared to other settings.

The centralized admission process was established in the late 1960s in combination with a new admission test (in the same spirit as the SAT) and a single-offer assignment mechanism based on a student-proposing deferred acceptance (DA) algorithm (Gale & Shapley, 1962; Abdulkadiroğlu, Pathak, & Roth, 2005, 2009).[7] The admission tests were redesigned at the beginning of 2000s and consist of a mandatory math and verbal exam, and one additional exam that could be science or history. Tests are taken simultaneously at a national level by the end of the academic year.[8] After scores are published (tests

[6]In 2012 and 2013 the selective system was composed by 33 universities, which represented around 60% of college students.

[7]It is surprising the lack of recognition given to Erika Grassau and her team in charge of implementing that reform, considering how ahead of time it was when compared with the boom of the implementation of DA mechanisms in the last decade.

[8]The Chilean academic year normally goes from March to December, but it is shortened to November in the last high school year

and GPA scores), students can start their application - exclusively online through the Department of Evaluation, Measurement and Educational Registration (DEMRE for its acronym in Spanish) website and without any monetary cost - by submitting a list with no more than ten programs, ranked in strict order of preference (their Rank Order List - ROL).[9] Once the application period is finished, the mechanism assigns students to schools using the deferred acceptance (DA) algorithm (Gale & Shapley, 1962; Abdulkadiroğlu, Pathak, & Roth, 2005).

Participation in the admission process is the only channel for students to enroll in any selective program.[10] Because students with higher application scores are more likely to be offered admission to a program than a student with a lower application score, and selection can only be based on that, it is considered a score-based meritocratic system. A program is considered more selective than others if the application score of the last student admitted - the program cutoff score - is higher. The application score is a weighted average of students' high school GPA and standardized test scores.

Deferred acceptance algorithm The Deferred Acceptance (DA) algorithm is the assignment procedure used to match students to programs, taking into consideration their preferences and the program vacancies.[11] The algorithm can be described as follows: In the initial step, each student proposes to their most preferred program listed in their ROL. Programs provisionally accept students based on their application scores until they fill their total number of seats, rejecting the rest. In subsequent cycles, rejected students propose to their most-preferred program among those that have not previously rejected them, and programs reject provisionally accepted applicants with lower application scores. This process iterates until all students are assigned to a single program or all unassigned

[9] To help applicants in their decision-making, DEMRE distributes a directory that provides an overview of the university admission process, key dates, information about vacancies, extra requirements, and the application score formula for each program for each university. While waiting for their results students can access a simulation mode site with a help video that explicitly states "when selected in one of the preferences all the following ones are eliminated, therefore it is very important the strict order of preferences from higher to lower personal interest."

[10] There are some special admission channels like switching students or students with disabilities but among those quotas admission score is always the selection criteria. This paper focuses on the regular admission channel.

[11] The variant of the student-proposing DA algorithm used by DEMRE establishes that all tied students for the last seat of a program must be admitted.

students have been rejected by every program they have ranked. See Rios et al. (2021) for a thorough description.

A studied theoretical characteristic of the DA mechanism is that it is strategy-proof, which makes reference to the fact that listing programs in order of true preferences is a weakly dominant strategy when students are allowed to rank every program, i.e. it cannot be manipulated by misrepresenting preferences (Dubins & Freedman, 1981; Roth, 1982). In the Chilean case, students are constrained to list only 10 choices, with extra conditions for some universities. [12] Table **??** shows that 90% of applicants rank less than 10 programs with a mode of 3, in which case truthful reporting is a dominant strategy (Haeringer & Klijn, 2009; Pathak & Sönmez, 2013). Assumptions over the rank order list and details about the assignment mechanisms are used to simulate admissions with and without the local context GPA measure. Section 2.1 discuss this procedure.

1.2 Local Context GPA Reform

The local context GPA reform provides the variation needed to study the effect of giving access to more selective programs to students who normally would not have access to them. The reform created a grade-based measure in the context of a meritocratic admission system, therefore a demographically neutral access-oriented intervention, which could be desirable in contexts where race or gender policies are restricted. The local context GPA measure (GPA^+) increases the application score through a boost, and makes students with good performance at their high schools more competitive ($\text{GPA}^+ = \text{GPA} + \text{relative boost}$). The way that the boost is constructed ensures that all well-performing students get a boost, but students from more disadvantaged schools -lower average GPAs- have a higher boost.

Equity concerns around college admission in the 1960s are what motivated the current admission system (meritocratic and transparent). Around the 2000s the admission test was changed in order to address socioeconomic differences in college admission but the socioeconomic gap in test scores persisted, even after controlling for income and parents'

[12] Universidad de Chile and Pontificia Universidad Catolica de Chile limit the applications to their programs, in order to be valid, to the first 4 preferences.

education. This evidence fueled a public debate that highlighted the need for a system able to identify high-ability students even when education conditions for them were not optimal to perform well in standardized test scores.

In the second half of 2012 academic year, the organization in charge of coordinating selective universities (CRUCH for its acronym in Spanish) informed the incorporation of a third element to calculate students' application scores in the 2013 admission process. The timing was such that students and programs had no scope for strategic responses, as students already have their GPA scores determined and universities have already made their capacity decisions.[13] Before the reform, application score (s_{ij}) for a student i to a program j was calculated as

$$s_{ij} = \alpha_j \text{Tests Scores}_i + \beta_j \text{GPA}_i$$

The weights α_j and β_j were chosen by the programs under some minimum restrictions defined by the DEMRE such that $\alpha_j + \beta_j = 1$.[14] After the reform was implemented, the GPA^+ measure was included in the formula

$$s'_{ij} = \alpha'_j \text{Tests Scores}_i + \beta'_j \text{GPA}_i + \gamma'_j \text{GPA}^+_i$$

with $\alpha'_j + \beta'_j + \gamma'_j = 1$. For its first year, γ'_j was fixed at a mandatory 10% for all the programs. From Figure 1 we can see that most of the programs opted for reducing the weight on β_j to allocate the 10% for the GPA^+ measure, therefore most of the variation observed in allocations comes from the introduction of the relative boost.

The proposed new component was designed to make more competitive the application of students that performed well at their high school by awarding them a boost to their GPA score if they perform above their school average ($\text{GPA}^+ = \text{GPA} + \text{relative boost}$). In Chile, grades are not fully curbed and they have an implicit reference to the minimum content expected by the national curriculum on each subject by year. Due

[13]The literal translation of the reform's name is "Ranking", which is misleading. Given that the score is assigned in relationship with the student's educational context rather than their class ranking, I will refer to it as local context GPA reform rather than Ranking reform.

[14]With a minimum 10% in each of the component.

to this, even the best student from a disadvantaged school that struggles to cover the minimum contents can have a very low GPA score. The GPA$^+$ component was designed such that with the boost, students that perform at the top of their school GPA distribution have a GPA$^+$ score that corresponds to that. By making the application score of good-performance students higher, the reform helped them access programs that would have rejected them when their application score was lower.

Local context measure in detail The local context GPA (GPA$^+$) measure is based on the GPA score of the student, but it is adjusted with a boost that depends on the historical average ($\overline{GPA}$) and the historical maximum high school GPA of their high school ($\max GPA$). The historical average and the historical maximum are constructed based on the high school GPAs of the students from the previous 3 cohorts at that school. It was chosen as a reference for the within-school measure to avoid within-classmates' competition. The formula to calculate the (GPA$^+$) score is the following

$$GPA_i^+ = \begin{cases} GPA_i & \text{if } GPA_i < \overline{GPA} \\ \overline{GPA} + \frac{850}{\max GPA}(GPA_i - \overline{GPA}) & \text{if } GPA_i \in [\overline{GPA}, \max GPA] \\ 850 & \text{if } GPA_i > \max GPA \end{cases}$$

Students with a GPA equal to or lower than the historical average at their schools have a local context GPA score equal to their GPA score. Students with a GPA bigger than the historical average but smaller than the historical maximum get their GPA score plus a boost that is determined by the slope of the line that connects the historical average GPA score with the historical maximum, which is for all schools the maximum possible score, 850.[15] This implies that students in this range, from a school with a more spread out high school GPA distribution will have a smaller boost in terms of score points for each extra point in their GPA. Finally, students that perform above the historical maximum

[15] Figure 2 correspond to an example to represent the relationship between GPA, GPA$^+$ and the boost.

at their high school get the maximum possible score (850), even if the GPA is, measured in application points, very low.

In order to simulate the admission assignment under the the new mechanisms defined by the inclusion of the GPA$^+$ for cohorts previous to the implementation of the reform I construct the GPA$^+$ measure for the cohorts 2009 to 2012. According to the reform, students who graduate from cohorts before 2009 or students who didn't attend a school had the local context GPA score equal to their GPA score.

1.3 Data

I focus my analysis on the entire universe of applicants to selective universities during the years 2012 (pre-reform) and 2013 (post-reform). For the first part of the empirical strategy, I construct a unique dataset that replicates college admission offers with and without the inclusion of the local context GPA measure in the admission process. This allows me to classify students into one of the three possible groups of analysis: pulled-up, pushed-down, or unaffected. To assess human capital acquisition, I supplement these statistics with annual enrollment and graduation rates from selected and non-selective colleges for all the applicants to the 2012 and 2013 process. Finally, I add to the analysis information on employment and earnings on the private labor market up to 10 years following their application.

Admission process The local context GPA reform was implemented in the admission process of 2013. For that reason, my analysis focuses on the short and medium-long-term outcomes of all the students that participated in the admission process that year and the year before (2012). I use information from students in the 2011 cohort to validate my research design strategy. [16] The first part of the empirical strategy leads to the classifications of students in each cohort in one of the three groups of my analysis: pulled-

[16]Even though information for later cohorts is available I don't consider it in my analysis because my empirical strategy is sensitive to the strategic behavior observed during those years. After 2013, some students switched schools in their last year of high school to improve their GPA$^+$ measurement. This potential for policy manipulation was fixed in the 2015 process.

in, pushed-out, and unaffected. Data on application preferences and application scores under status quo (pre-reform) and under the local context GPA (post-reform) regime are the main requirements for this procedure.

Administrative data at the student level from the admission process was shared upon request by DEMRE. It consists of socioeconomic and demographic information of applicants (gender, date of birth, self-reported family income, and parents' education), applications scores (tests scores, GPA, and local context GPA score), high school characteristics, application information (rank order list of program preferences listed in the application with their final status: valid/invalid, offer/no offer and waitlist), and enrollment information (program, application score, and ranking of preference). This information is mainly used to simulate students' admission under a mechanism that uses two (test scores and GPA) or three (test scores, GPA and GP^{+}) inputs to calculate the application score.

The "new" mechanism incorporates the local context GPA measure (GPA^{+}) into the application score formula. To compute the local context GPA measure for cohorts before the reform I use information from the national school records on high school performance for the entire population of high schoolers between 2002 and 2011 which is available online at the data platform of the Department of Education.[17] I compute the historical average and the historical maximum GPA at each school for each graduation cohort, and then the local context GPA score for students who graduated between 2008 to 2012 in the 2011 and 2012 admission process.[18] Figure 3 shows a binscatter graph with the boost score - i.e. the extra score relative to GPA- of the local context GPA score for students in application cohorts 2011 to 2013. The x-axis is the GPA score of the student minus the historical average high school GPA at the school of the student, therefore on the positive numbers we see the boost score in application points. Note that 2013 data is directly reported by DEMRE and 2011 and 2012 was calculated using the local context GPA score formula.

I also constructed a dataset with program characteristics like application score weights,

[17] `https://datosabiertos.mineduc.cl`

[18] Students can participate in the admission process as many times as they want. The proportion of freshmen and older applicants is around 60% to 40% in each cohort.

application score restrictions, and the total number of seats from the public newsletter with the official information. Application score weights are required to calculate the application score under the two regimes. For each program, application scores under the status quo regime (s_{ij}) are calculated using weights from the 2012 process, and application scores under the GPA$^+$ regime (s'_{ij}) are calculated with 2013 weights.[19]

Enrollment and graduation outcomes To measure the effect of the reform on educational outcomes I track all the students that participate in the application processes of 2012 and 2013 using yearly information on enrollment and graduation provided publicly by the Department of Education. From the admission data I can observe who got an admission offer and to which program. I create variables to indicate if a student enrolls in their admission offer or if they enroll in a non-selective college instead. By using the enrollment file in the second year ($t = 2$) I can check if the student persisted at their admission offer, if they re-apply or switched to a different selective program, if they switched or persisted in a non-selective college, or if they dropped out of college.

Additionally, for each application cohort, I track graduation by 6th, 7th, and 8th years after application because yearly graduation files were available only up to 2020. I construct 3 graduation measures: (1) program graduation or graduation from the admission offer in 2012 or 2013, (2) graduation from some selective university to take into account that students that don't get their desired admission may switch or re-apply in the following years, and (3) graduation from a non-selective college which is always an alternative. Having access to data of the entire system allows me to measure the complete impact of the reform in the selective system - the one that DEMRE attempt to coordinate-, as well as the impact on the entire college system.

Labor market outcomes To study the effect on earnings of giving access to better programs to students that normally couldn't access them I use information from the Unemployment Insurance (UI) data. The UI data has information on all the dependent

[19]Music, arts, and acting programs require an additional aptitude test, which score is not reported separately in the data. For those cases, the application score used for the alternative regime was the same as the one reported originally.

workers over 18 years old that participate in the private sector.[20] All the information is aggregated at the treatment group level. For pulled-up, pushed-down, and unaffected students I observe the fraction that was present in the labor market (participation) and bins for their monthly taxable income from 8 to 10 years after the admission process.

2 Empirical Strategy

The empirical strategy is divided in two parts. First, I simulate the admission mechanisms with and without the local context GPA measure. I classify students into 3 groups based on the admissions simulations: (i) pulled-up, students who gain access to more selective admissions when the third component is considered in the assignment mechanism, (ii) pushed-down, students who loss access to more selective programs with the new mechanism, and (iii) unaffected, students whose admission options are unaffected by the change in the mechanism. By simulating the admissions under the two mechanisms in earlier years, before the reform was implemented, I can identify the groups who would have been pulled-up and pushed-down in those years. This facilitate a difference-in-differences design to estimate the impact of the inclusion of the relative GPA on enrollment, graduation and earnings for the students affected by the reform.

2.1 Identification of treatment groups: pulled-up, pushed-down and unaffected

The inclusion of the local context GPA measure into the admission process enhanced the equity of the college admission system. Students with relatively low test scores but high GPA from low-educated and low-income families got admissions into more selective program when the third component (GPA$^+$) was considered. There is also a higher representation of females in the pulled-up group of students. Pushed-down students tend to be in higher proportions from private schools, males, and from highly educated and

[20]Data excludes: (i) workers subject to an apprenticeship contract; (ii) workers under 18 years of age; (iii) private home workers (until October 2020); (iv) pensioners; (v) independent or self-employed workers; and (vi) public sector workers. In a future version of the research, I will be able to include information on public sector workers and person-level data.

high income families. In terms of the characteristics of the changes in the admission offers induced by the reform, most students affected had an admission one preference up or down with respect to the status-quo regime and most students get a new admission in the same field.

Simulation of the admission mechanism The local context GPA reform impacted the way that students were matched to the programs that they apply. Before its implementation the application score for a student i, applying to a program j was calculated using only 2 inputs: admission test scores e_i and GPA score g_i. With the implementation of the reform the new application score was calculated based on $s'_{ij}(e_i, g_i, c_i)$. Denote $\mu(\cdot)$ as the matching function defined by the mechanism that uses a Deferred Acceptance algorithm, the information from the pool of applicants, the application scores defined by the programs and the capacity restrictions of the program. The change in the inputs used by programs to evaluate students defines a new mechanism $\mu'(\cdot)$.

A student i can be characterized by $\theta_i(\succ_i, e_i, g_i, c_i)$ composed of their rank order list ($\succ_i$) and their scores. In each application year, for some students the admission assignment under both mechanisms will differ, $\mu(\theta_i) \neq \mu'(\theta_i)$, and for others it won't $\mu(\theta_i) = \mu'(\theta_i)$. I classify the pool of applicants into 3 mutually exclusive groups:

- Pulled-Up: $PU_i = 1\{\mu(\theta_i) \prec \mu'(\theta_i)\}$ students who get access to a program ranked higher in their list with the new mechanism μ' than with the old mechanism μ.
- Pushed-Down: $PD_i = 1\{\mu(\theta_i) \succ \mu'(\theta_i)\}$ students who get access to a program ranked lower in their list with the new μ' than with the old mechanism μ.
- Unaffected: $C_i = 1\{\mu(\theta_i) = \mu'(\theta_i)\}$ corresponding to students with access to the same programs with and without the inclusion of the GPA$^+$ measure.

Implementation of admission simulations For each student, in each application process, I start by computing their alternative application score. For students pre-reform this also includes computing the GPA$^+$ measure. For each program that the student listed, I use the weights from 2012 and 2013 to calculate the alternative application score (for students in the 2012 cohort I calculate s'_{ij} and for students in 2013 I compute s_{ij}).

I replicate the DA algorithm to simulate the admission assignment of students with the GPA$^+$ measure for pre-reform students ($\hat{\mu}'(\theta_i)$), and without it for post-reform students ($\hat{\mu}(\theta_i)$). In order to test the quality of the replication I simulated the admission assignments using s'_{ij} for cohort 2013; I replicate 99.9% of the real assignment offers.

For each student in application cohort 2012 or 2013, I compare the simulated with the real assignment offer and I classify them into the pulled-up (pushed-down) group if the admission assignment with the GPA^+ measure was higher (lower) in the list than the assignment without it. Students are classified as unaffected if the admission program under both regimes is the same.

Simulation assumptions There are three main assumptions needed for the simulation to be valid as a counterfactual under the alternative mechanism.

Assumption 1 *The rank order list of preferences that the students submit would have been the same with and without the reform*

Assumption 1 has two components, one that refers to the stability of preference and one that refers to the reporting behavior. I assume that preferences are stable with respect to the reform, which means that the indirect utility associated with each program does not depend on the components and weights used by the programs to evaluate applicants.

In terms of reporting behavior, I use the traditional approach taken by the literature that establish that without restrictions on the number of applications, the dominant strategy with a Deferred Acceptance (DA) algorithm is truthful reporting (Gale & Shapley, 1962; Dubins & Freedman, 1981; Roth, 1982). As most of centralized admission system, the Chilean application system restrict the application list (up to 10 options), however, because more than 90% of the students list fewer than 10 options, the restrictions can be interpreted as not binding (Haeringer & Klijn, 2009; Abdulkadiroğlu & Sönmez, 2003; Abdulkadiroğlu, Pathak, Schellenberg, & Walters, 2020).

One possible concern with respect to the reporting behavior arise from the most recent literature on mechanisms design and their interest on properly using the information from the centralized admission systems to estimate school choice demands (Agarwal et al., 2020; Fack et al., 2019; Larroucau & Rios, 2018). One way of rationalizing the fact that students don't fill up their application options relates to the idea that reporting behavior is based on students' feasible options. This behavior may violate assumption 1 if students that observe the boost (that potentially could increase their feasible options) reacted by adding more selective programs to the top of their list. This would create a problem in the identification of the treatment group if students get admitted to this added programs but similar students that didn't observed the boost (cohort of 2012) didn't get admitted under the simulation (because they didn't list the new options).

To assess this potential threat I first compare the number of admission options listed in 2012 and 2013 by students with a boost (by adding a program to the top of the list, the total number could increase). Students that observe the boost in 2013 are not more likely to have longer application lists than students with the same calculated boost but who didn't observed it (cohort of 2012). Additionally, I check the selectivity of the most preferred program or top ranked program of students with a boost, in 2012 and 2013. Figure 4 show that the selectivity of the first option increase in 2013 only in the highest values of boost score. In order to check for the sensitivity of the results I estimate the results without students with more than 150 points in their boost score (2% of the total sample). As discussed in Section 3.4, results don't change qualitatively or quantitatively with this sample restriction.

Assumption 2 *The number of available seats per program each year would have been the same with or without the reform*

Assumption 3 *The number of available seats per program each year would have been the same with or without the reform*

Assumption 2 and 3 are justified by the fact that the reform was announced in the last half of the academic year. At that point, universities have already made their capacity decisions and students' average GPA from the 4 year of high school was already determined, therefore there was no scope for strategic responses.[21]

Characterization of treatment groups Table 1 shows the characteristics of the group of students identified as pulled-up, pushed-down and unaffected for cohorts of applicants in 2012 and 2013. Each year, pulled-up and pushed-down applicants account for approximately 4% of the applicant pool. From Table 1 we can see that the reform was able to impact the students that were targeted by it. Students in the pulled-up group have better GPA than those in the unaffected and pushed-down groups; yet, their exam scores are comparable to those in the unaffected group. Looking at pushed-down students, they have low GPA and high test scores. Moreover, pulled-up students are 3 times less likely to attend a private high school than a pushed-down student and looking at family characteristics, pulled-up students come from families with average income 30% lower than pulled-up students, and their parents are less educated.

Figure 5 presents the distribution of pulled-up and pushed-down students based on the number of positions moved in their rankings between the admission assignment with and without GPA$^+$. If the most preferred program that the student could reach without the GPA$^+$ measure was choice 3, but with the inclusion of the boost the student could get into their most preferred option (pulled-up students), then the student was moved 2 positions due to the reform. From Figure 5 we can see that the change in terms of preferences is similar for pulled-up and pushed-down groups.

A more detailed analysis of the distribution of rankings for admission is presented in Table 2. Each raw presents the number of students with admission assignments in that ranking when the local context GPA measure is considered. Each column presents that total number of students with admission assignment in that preference choice when the GPA$^+$ measure is not considered. Students assigned to the same program in both regimes are classified as unaffected and are presented in the table without background color (table diagonal). The percentage value in each cell correspond to the proportion

[21]After the first year, there is some evidence, at least anecdotal, about students switching schools in their last year in order to graduate from schools with very low maximum historical GPA in order to gain the maximum score from the GPA$^+$ component. In 2015 this problem was addressed with a change in the policy, which established that the score was calculated relative to the GPA of the student and the school that they attended each year.

of students in that group in that specific ranking combination. The main margins of treatment of the reform corresponds to movements along preferences 1 and 2, preferences 2 and 3, preferences 1 and 3, and between preference 1 and no admission offer. The high percentage of students moved along this last margin is not explained by a higher proportion of students with shorted rank order list but rather due to the a bigger proportion of students at the margin of the minimum requirements of not very demanded programs. More specifically, certain program establish complementary restrictions to admission, as minimum application scores (taking all the components into consideration) or minimum test score averages. Students in this margin have twice higher proportion of their total rank order list as invalid.

Finally, Tables 4 and 3 present the number of pulled-up and pushed-down student in each field with and without the inclusion of the GPA^+ component, based on the fields of the admission and simulated admission. In both cases, in most of the cases, students move along their ranking but they stay in the same field (diagonal of the table).

2.2 Difference-in-differences design

I estimate the effect of the reform on human capital acquisition and productivity, on the group of pulled-up and pushed-down students. My difference-in-differences design compares the outcomes of students who were affected by the reform versus those who weren't, before and after the inclusion of the local context GPA measure. Comparing the change in outcomes for these two groups across the two periods allows me to control for transitory variation in outcomes that happen due to factors that are unrelated to the reform. With the estimation of the effect of the reform on pulled-up and pushed-down students, I analyze the (outcome) efficiency impact of the reform on the system.

The parameters of interest to evaluate the effect of the inclusion of the local context GPA measure in the admission process can be expressed as the conditional average treatment effect for the group of students pulled-up and pushed-down.

$$\tau(PU) = \mathbb{E}[Y_i(\mu') - Y_i(\mu)|PU_i = 1]$$
$$\tau(PD) = \mathbb{E}[Y_i(\mu') - Y_i(\mu)|PD_i = 1]$$

In the potential outcome framework $Y_i = D_i Y_i(1) + (1 - D_i) \cdot Y_i(0)$ is the outcome of a student i, and $D_i = 1\{\text{when the relative GPA is used for admission assignment}\}$. The observed outcomes is represented by $Y_i = 1\{t(i) = 2012\} \cdot Y_i(0) + 1\{t(i) = 2013\} \cdot Y_i(1)$. Assuming additive separability to capture any changes in time uncorrelated to the determinants of the outcomes with and without the inclusion of the GPA$^+$ measure, I estimate models of the form:

$$Y_i = \beta_1 PU_i + \beta_2 PD_i + \beta_3 (PU_i \cdot Post_i) + \beta_4 (PD_i \cdot Post_i) + \beta_5 Post_i + X_i' \Gamma + \varepsilon_i$$

where Y_i is the outcome variable of interest to evaluate the reform: enrollment, graduation and earnings. PU_i indicates if the student belong to the pulled-up group, PD_i indicates if the student belong to the pushed-down group, $Post_i$ is an indicator that takes the value of 1 if the students apply post reform. The omitted group is the group of students that get access to the same programs under both regimes. X_i' is a vector of individual characteristics such as gender, family income, type of school, GPA and standardized test scores to control for possible changes in the composition characteristics of pulled-up and pushed-down students between 2012 and 2013. ε_i is an idiosyncratic error term.[22]

Here β_3 and β_4 are the estimators of the parameter of interest to evaluate the reform. β_3 capture the effect on outcome Y_i of gaining access to the a more preferred, but also more selective program due to the inclusion of the GPA+ measure in the admission process. Likewise, β_4 capture the effect of losing access to more selective programs with the reform.

[22]Results are presented with and without controls. Most of the results are quantitatively and statistically unchanged.

Identification assumption The key identification assumption is that the outcomes for these three groups of students would have evolved similarly between 2012 and 2013 cohort if the reform would have not been implemented. I cannot directly test that, however, I conduct a placebo exercise with data from the 2011 application cohort that present suggestive evidence in support of it.

Following the same procedure used for cohort 2012, I start by computing boost score for each student in 2011, and application scores for each program in their rank order list. With that, and keeping constant the vacancies observed that year I re-run the DA algorithm, using the three components application score. Using the simulated admission assignment I classify 2011 students into pulled-up, pushed-down and unaffected. Finally, I estimate the diff-in-diff specification but with the variable $Post_i$ indicating if the student was observed in 2012.

Table 5 shows the estimates for this placebo exercise, which can be interpreted as the effect in enrollment and graduation for pulled-up and pushed-down students when no reform is implemented. As expected, there is no significant effect, suggesting that when no reform is implemented these groups follow a similar trend. The estimates would be biased if the coefficients of interest reflect sample selection resulting from the impact of the reform on the composition of applicants. However, there is no change in the trend of total applicants, and no change in the probability of pulled-up students to reapply compared with the 2011 cohort. There also would be bias in the estimates if there were unexpected changes in 2013 in other determinants of outcomes that differentially affected the three groups. I am aware of no such change.

Notably, the intervention considered for this diff-in-diff evaluation occurred just once, so considerations regarding the calendar time of the comparison group observations, such as those stated by Goodman-Bacon (2021); Baker et al. (2022); De Chaisemartin & d'Haultfoeuille (2020), do not apply in this context.

3 Results

I find that the introduction of the local context GPA measure into admission scores improved the system's equity without sacrificing its efficiency. The increase in equity comes from the finding that pushed-up students are more likely to enroll and graduate from more selective programs. This access to more selective programs translates into higher earnings, which I interpret as an increase in productivity. I infer that there is no efficiency loss due to the change in the admission test scores from the fact that, even though pushed-down students enroll later in the selective system and have lower completion rates, there is no negative effect on earnings.

3.1 Enrollment

Enrollment at selective universities can only occur at the program to which students are admitted with the deferred acceptance algorithm. Thus, they enroll in their most preferred program among the ones they are eligible for based on their application scores and the applications and scores of the other students. If the student chooses not to enroll in the program, they can (i) enroll in a non-selective college, (ii) re-apply the following year (normally after taking extra test preparation courses), or (iii) decline to attend college.

Table 6 shows the average enrollment rates in the selective system for the 3 groups and preview the diff-in-diff results from Table 7. Difference-in-differences estimate for pulled-up students shows a large effect in the probability of enrollment. After the reform, pulled-up students are 22 p.p. more likely to enroll in the selective program that they were admitted. This is a 40% effect on enrollment. For pushed-down students the probability of enrollment decreases by 16.7 p.p. The difference between the effect on pulled-up and pushed-down students is significant, indicating that the inclusion of the GPA$^+$ measure improved the system in terms of identifying successful applicants.

Figure 5 shows that most of the students in the pulled-up and pushed-down group were moved only one position in their rank order list when the GPA$^+$ measure was included.

Table 2 complements this figure by showing the information disaggregated by ranking. More specifically, Table 2 shows the distribution of 2013 applicants based on the ranking of their admission assignment with GPA$^+$ and without it. The table has the total number of students for each combination of rankings and the proportion relative to the treatment group. For example, students that are admitted to a program that they rank in position 1 with the GPA$^+$ measure and to rank 2 without it - therefore pulled-up - represent 26% of pulled-up students. We have a similar proportion for the symmetrical problem of pushed-down (from rank 1 without to rank 2 with the GPA$^+$).

The large enrollment effects presented above can be driven by changes at two margins: extensive and intensive. On the extensive margin, the reform changed the probability of a student of getting access to some selective program in pulled-up and pushed-down students by approximately 20%. To study the intensive margin, I use the original specification and the simulation of admission assignments, but I restrict the sample to students that would have got some admission under the two regimes. This corrects for the potential selection bias of only observing enrollment if a student actually gets an offer. [23] Table 8 shows the results from this exercise. The estimates on enrollment for pulled-up students after the reform is smaller (17 p.p.) but still large. Compared with the pushed-down students (11 p.p.), I find evidence of higher intensity of preferences for pulled-up students, i.e. that the reaction, in terms of enrollment decision, from getting access to a program higher in the rank order list is stronger than the reaction from losing access to it, for the pushed-down group.

I summarize the changes in the programs that students attend using traditional measures of quality like selectivity and graduation rate. Table 9 shows how the characteristics of the peers and programs that students attend before and after the reform changed. Columns 1 and 2 show the differences-in-differences estimates of a regression in which the dependent variable in one of these average program characteristics before the reform. The first 3 rows show that pulled-up students attend more selective programs after the

[23] All students in the pulled-up group got an admission offer in 2013 (if not they could not be better than without the GPA$^+$ measure), but not all got an admission offer in 2012 because the reform was still not implemented.

reform, in the sense that the average student at the program that they enrolled had higher test scores and GPAs than the average student at the programs they enrolled before the reform was implemented. Graduation on time is an indicator of the probability that a student graduates in the number of years set by the program; after the reform pulled-up students enroll in programs where the average student is more likely to graduate on time. The results are symmetrical for pushed-down students. [24]

Enrollment by second year after application

Given that not all the students enroll at the program that they get admitted in the selective system, it is interesting to study how the alternative options change with the implementation of the reform. Columns 3 and 4 in Table 7 show that in the first year, pushed-down students compensate for the decrease in the probability of enrolling in a selective program by enrolling in the non-selective system. However, the 3.9 p.p. increase in the probability of enrollment in the non-selective system does not offset completely the decrease in the probability of enrollment in the selective system. This means that the reform leads to some pushed-down students not enrolling in any university in the first year after high school.

Table 10 shows the results from the same diff-in-diff exercise when the outcome variables are: for columns 1 and 2, an indicator if the student is enrolled in any program (selective or non-selective) by second year, and for columns 3 and 4, an indicator for enrollment in a selective program by second year. After controlling for observable characteristics, pushed-down students are not less likely to acquire college education after the reform; however, when looking at enrollment in the selective system there is still a gap relative to before the inclusion of the GPA$^+$ measure. The probability of enrollment (by second year) is a mix of the effect on enrollment in the first year and the effect on the enrollment in the second year if the student reapplies. This effect for pushed-down students is 5.2 p.p lower, which is a smaller effect than in the first year. This indicates that students in the pushed-down group are more likely to be moving through college with

[24] The expected graduation time of the programs that pushed-down students enroll after the reform are on average 0.07 years shorter.

at least one year of delay. Table 11 corroborates this point, showing that pushed-down students are 7 p.p. more likely to reapply to the selective system after the reform was implemented.

3.2 Graduation

I begin by analyzing the impact of the inclusion of the local context GPA measure on program completion. Because pulled-up students get access to more selective programs with the reform, I can test the mismatch hypothesis and examine the potential impact of this on human capital acquisition. Then, I examine the effect on overall college completion by examining the likelihood that a student in each group will graduate from college, regardless if it is the program that they got admitted in the application process. Given the enrollment dynamics, I also consider the possibility that students are still enrolled eight years after application.

Program completion

Columns 1-3 of Table 12 presents the results for graduation from the admission program for pulled-up and pushed-down students at different points in time. Consistently, there is a positive effect (8.4 p.p. increase by 8 years after application or 36% effect) on the likelihood of graduation from the admission program for pulled-up students. Column 4 also shows that pulled up students are more likely to graduate on time after the implementation of the reform. For pushed-down students the effects on graduation are similar in magnitude on the opposite sign.

Table 13 show the same results in the restricted sample of students that had an admission offer with and without the inclusion of the GPA$^+$ measure. From here we can see that the effects are not driven only by the fact that after the reform students are more or less likely to get admission offers into some selective program. When the sample is restricted to students with admission offers with and without the inclusion of the local context GPA measure the probability of graduation from the program of admission for pulled-up students increases by 7.8 p.p. Table 13 show the results for graduation in the sample of enrolled students. However, because I don't have a model to control for selection into enrollment these results are biased. It's expected that because pulled-up students in 2013 are more likely to enroll, even comparing students with admission offers under both regimes, the sample is negatively selected. The zero effect on graduation for pulled-up students suggests that this is correct.

In essence, the reform enabled pulled-up students access to more selective programs which increased their likelihood of enrolling in and graduating from those programs. Putting the graduation effect for pulled-up students into perspective, the implied graduation rate for the marginal student admitted by the local context is 38% (8.4/21.9). This does not differ much from the average graduation rate of unaffected post-reform (40%) or from the pre-reform level of 39% percent. In addition, the impacts are qualitatively comparable to the findings of other equitable college admission programs, such as Bleemer (2021) and Black et al. (2020).

Mismatch hypothesis The mismatch hypothesis established that applicants with lower test scores targeted by equitable admission policies would benefit from enrolling in less selective universities, where their academic qualifications more closely "match" those of their peers (Sowell, 1972). This hypothesis found empirical support on some of the mixed results from the research around affirmative action policies (Arcidiacono & Lovenheim, 2016). The evidence discussed earlier for the local context GPA reform contradict this hypothesis; the fact that students in pulled-up groups enroll in more selective programs after the reform, and their increase in the probability of program completion is evidence against the mismatch hypothesis.

However, because the main specification doesn't control for the tuple of admission programs with and without the reform, one possible concern refer to the potential imbalances on the programs that student get admitted with and without the reform, between 2012 and 2013.[25] In order to control for that, I run an alternative specification that in-

[25]Students in the pulled-up group are by definition admitted to more selective programs post-reform,

cludes as a covariate the admission assignment without the reform. This way, I can ensure that all the variation captured by the diff-in-diff comes from pulled-up students with the same admission assignment without the reform and with more selective programs after the reform.[26] Table 15 shows the result from this exercise. Contrary to the mismatch hypothesis, more selective admission increased the graduation probability for pulled-up students.

STEM Arcidiacono et al. (2016) find that marginally admitted students in California are less likely to graduate in science (STEM) majors.

College completion

Table 17 shows the average graduation from any program by 6, 7, and 8 years by treatment groups, before and after the implementation of the local context GPA reform. It is especially important to notice that graduation from any program captures some of the indirect effects of the reform in reapplications (therefore late enrollment in the selective system) and enrollment in the non-selective system. This could be one of the reasons why, even 8 years after the application, there are still important changes in the graduation rates compared with the previous year, which suggest that the lack of more graduation data limits the full analysis of the reform.

The difference-in-differences estimates for the effect of graduation from any program are presented in Table 18. There is no change in college completion for pulled-up and pushed-up students by 7 year after application due to the reform. However, there is a negative effect on graduation by 8 years for pushed-down, i.e. after the reform they are less likely to have completed some program. Because this result could be reflecting the fact that pushed-down students are more likely to graduate late (due to late enrollment after the reform) or the fact that pushed-down are acquiring less human capital after the

but this is relative to their own assignment.

[26]Remember that the definition on pulled-up group is based on the ranking of the preference, but if something was ranked higher and was less selective than the admission assignment without the GPA^{+} measure, then the algorithm would have assigned the student to that program pre-reform.

reform, column 4 of Table 18 present the result when the dependant variable indicates if the student graduate or is still enrolled 8 years after application. The null effect implies that pushed-down students are not acquiring less human capital after the reform.

Table 20 present the results divided by graduation from any selective program and any non-selective program. These results also suggest that changes in graduation at 8 years after application for pushed-down students is driven mostly by changes from selective enrollment, which require a late enrollment if the student wants to enroll in a different program than the admission assigned by the new mechanism after the inclusion of the local context GPA measure.

In summary, the reform made pulled-up students more likely to graduate from more selective programs, with no impact in college completion. For pushed-down students, the inclusion of the GPA$^+$ made them less likely to graduate 8 years after application, however, this is not due a decrease on the probability of college completion but due to a delay enrollment in selective programs, for some of the students that didn't enroll or didn't stay in the program admitted after the reform.

Intensity of treatment

Heterogeneity

3.3 Labor Market Outcomes

Finally, I study the labor market effects of the reform.[27] An important challenge refers to the long graduation times observed in the previous section. This fact limits the earnings analysis 10 years after application. Additionally, aggregated data - earnings with an indicator of group of treatment but without individual characteristics- only allow for very preliminary evidence at group level.

Figure 6 present earnings histograms for the pulled-up and pushed-down students

[27]Up to this date, access to individual level data required to estimate the difference-in-differences specification used in the previous sections is under approval.

pre and post implementation of the local context GPA reform. In each case histograms are presented relative to the unaffected group. Even though, at the moment I cannot calculate the difference-in-differences estimates, a preliminary review of the aggregated data confirms that pulled-up and pushed-down students do not do worse than before the implementation of the reform. In terms of outcome efficiency, the evidence confirms that the new assignment mechanism didn't make the system less efficient.

3.4 Robustness checks

I conduct a number of checks to verify the robustness of my conclusions. I check different samples (removing students with boost higher than 150 points, only freshman applicants, or students attending programs over 6 years) and estimation strategies and all of them support my main findings.

Changes in ROL due to the reform The key assumption for the identification of pulled-up and pushed-down groups is that the rank order list (ROL) of application submitted by the applicants in each process would not change under an assignment mechanism. Concerns over inclusion of more selective programs when boost observed. By looking at the cutoff score of the program listed in the first preference in 2012 and 2013 for students witht the same boost we see some increase in the selectivity when boost is larger than 150. As a robustness check I estimate the main results but removing students with boost score higher than 150.

Changes in pool of applicants due to the reform I conduct the analysis in two samples: all applicants and only freshmen applicants.

Sensitivity of the results to long programs Another con

Inference The results presented so far are estimated using robust standard errors. As an alternative Appendix E present the main results allowing for clustering at the school level. However, any of the results account for the error deriving from the estimation of the the pulled-up and pushed-down groups. Results are nearly identical to the alternative assumptions on the variance and covariance matrix.

4 Alternative approach

5 Conclusion

This paper studies the impact of providing students with access to more selective college alternatives. I use the variation on admission generated by the inclusion of a local context GPA measure motivated by equity concerns. I explore the effects of the variation on enrollment, graduation and earning for the two groups directly and indirectly affected by this change: (i) students who gain access to more selective programs (pulled-up) and (ii) students who lose access to more selective programs (pushed-down).

Using a difference-in-differences design I can compare the outcomes of students in the pulled-up and pushed-down groups before and after the implementation of the reform, therefore, before and after they get access to these more selective programs. The transitory variation on outcomes is controlled by the second difference with respect to the group of unaffected students. The transparency of the college admission process combined with the properties of the assignment mechanism and the richness of the data available allow me to cleanly identify the groups of students affected by the reform, one of the big challenges in the evaluation of admission reforms.

I find that the incorporation of the local context GPA measure into the college admissions application score formula expanded the options available for students with significant less resources. As a result of the reform, pulled-up students became more likely to enroll in a selective program, and they chose to enroll in programs where their peers have higher test scores, GPA scores, and graduation rates. Contrary to the prediction of the mismatch hypothesis, reform-targeted applicants with lower test scores gained from enrolling in more selective options, boosting their likelihood of graduation by 8.4 percentage points.

For pushed-down students, I find that their likelihood of graduating from the admission program assigned by the new mechanism decreases by 8.2 p.p., but they are not less likely to receive a bachelor's degree. There is however an impact in the timing of their enrollment that would be interesting to study with more details once more data on graduation and earning becomes available. Nevertheless, preliminary evidence confirm that there is no negative impact on earning for pushed-down students.

Collectively, the evidence presented above indicate that test-based meritocratic admission system can be improved by the inclusion of in-school performance metric, increasing admission equity without incurring an efficiency penalty.

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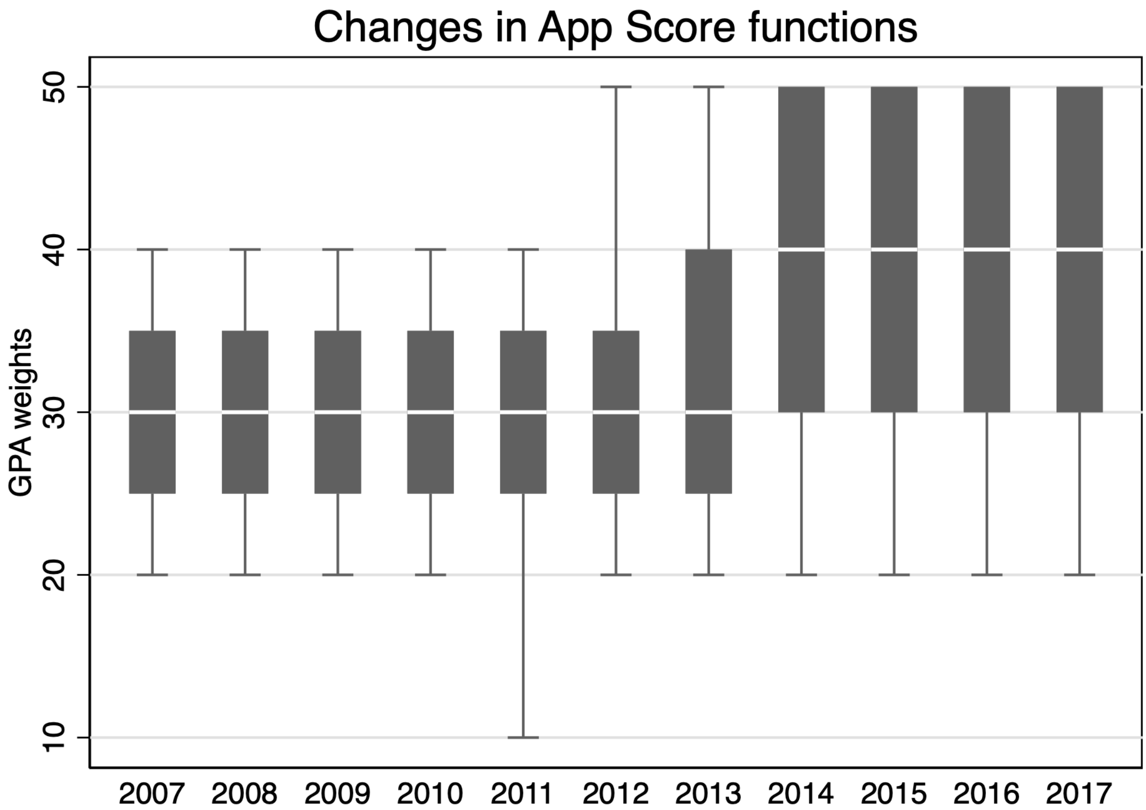
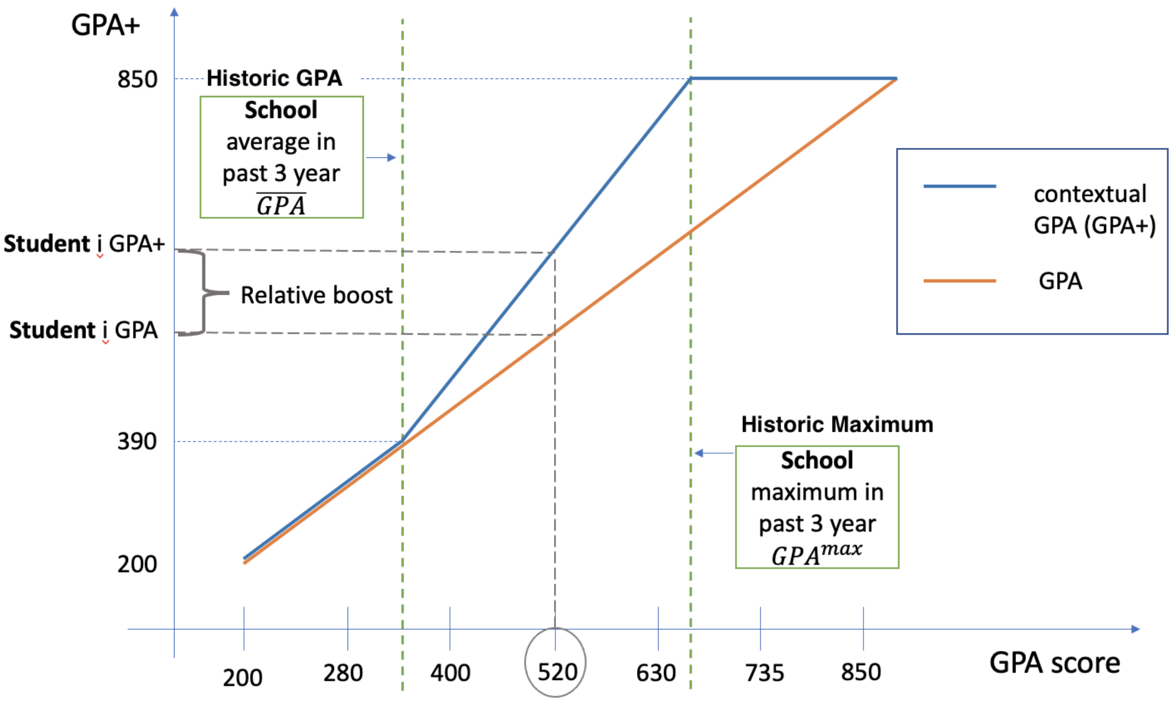
Figures and Tables

Figure 1: Weights of GPA components (GPA + GPA$^+$) in application scores by year



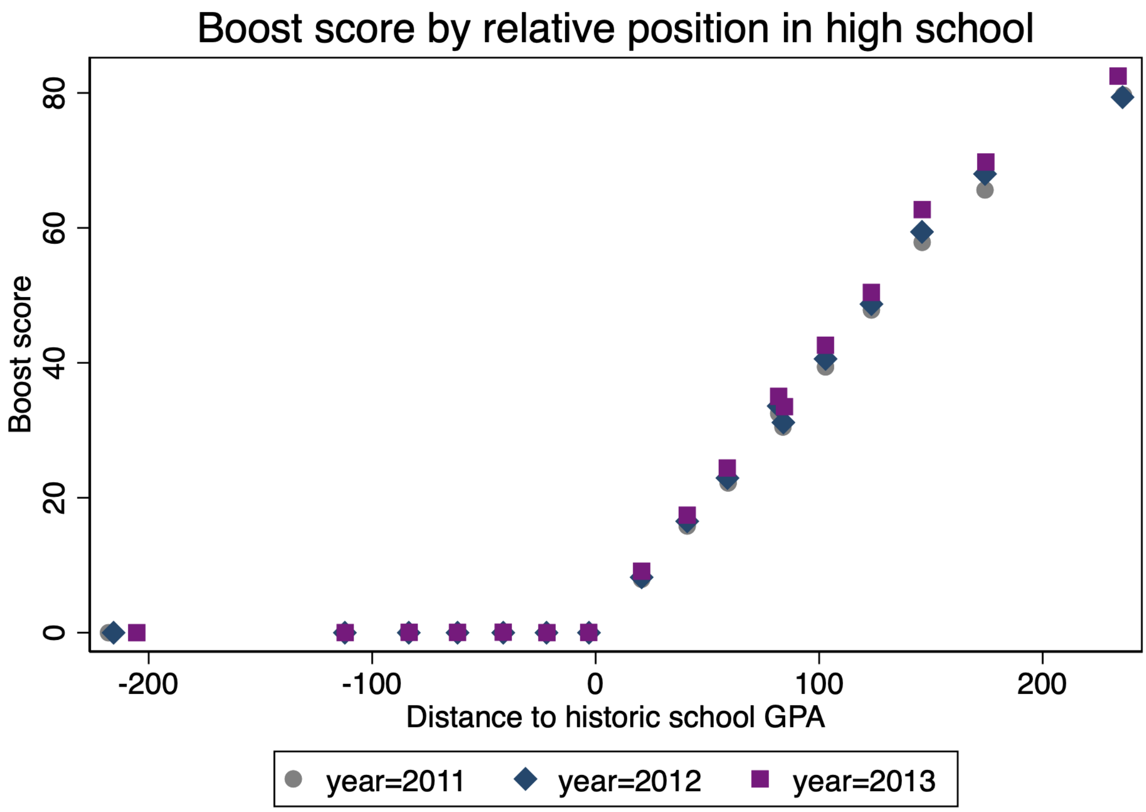
Notes: This figure shows the whisker plots for the distribution of the weights of the GPA components assigned by programs in the application score formula. The middle box represents 50% of the data, the white line corresponds to the median weight and the maximum and minimum values are displayed with vertical lines ("whiskers") .

Figure 2



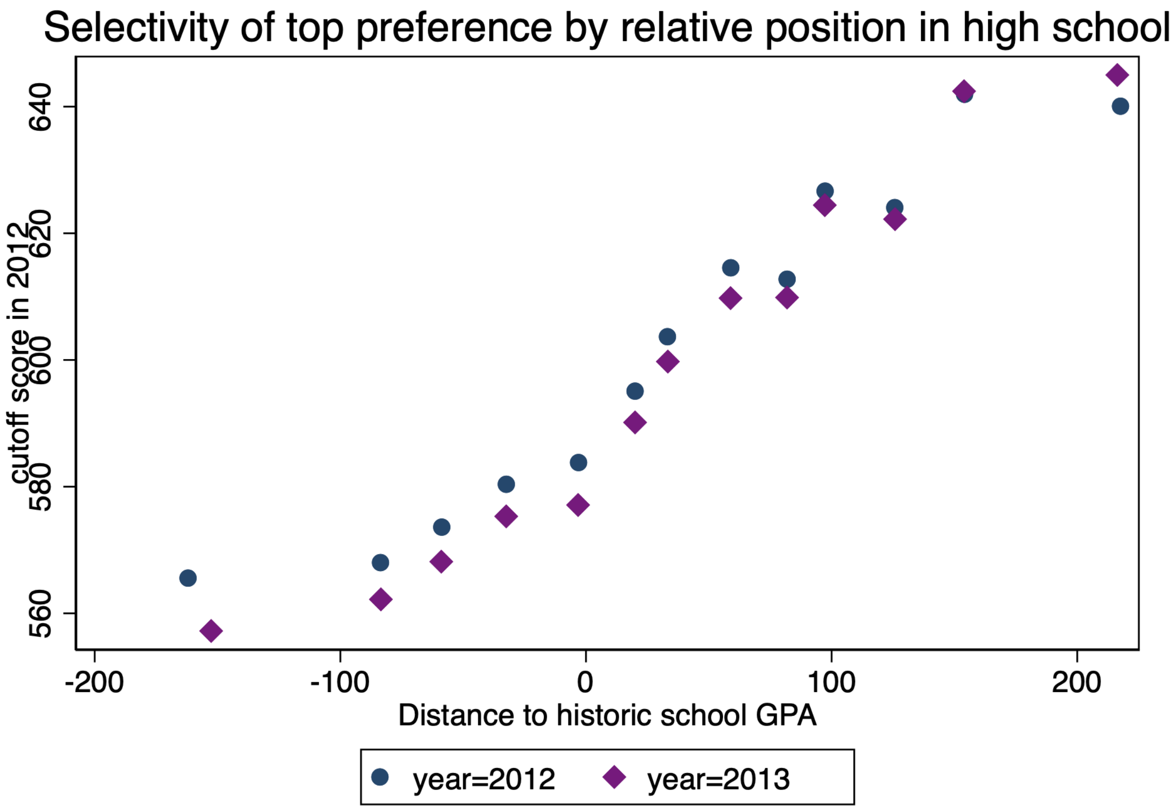
Notes: exemplary figure to show how GPA$^+$ depends on school averages and how it relates to the GPA score. Boost is obtained from the difference between GPA$^+$ score and GPA.

Figure 3



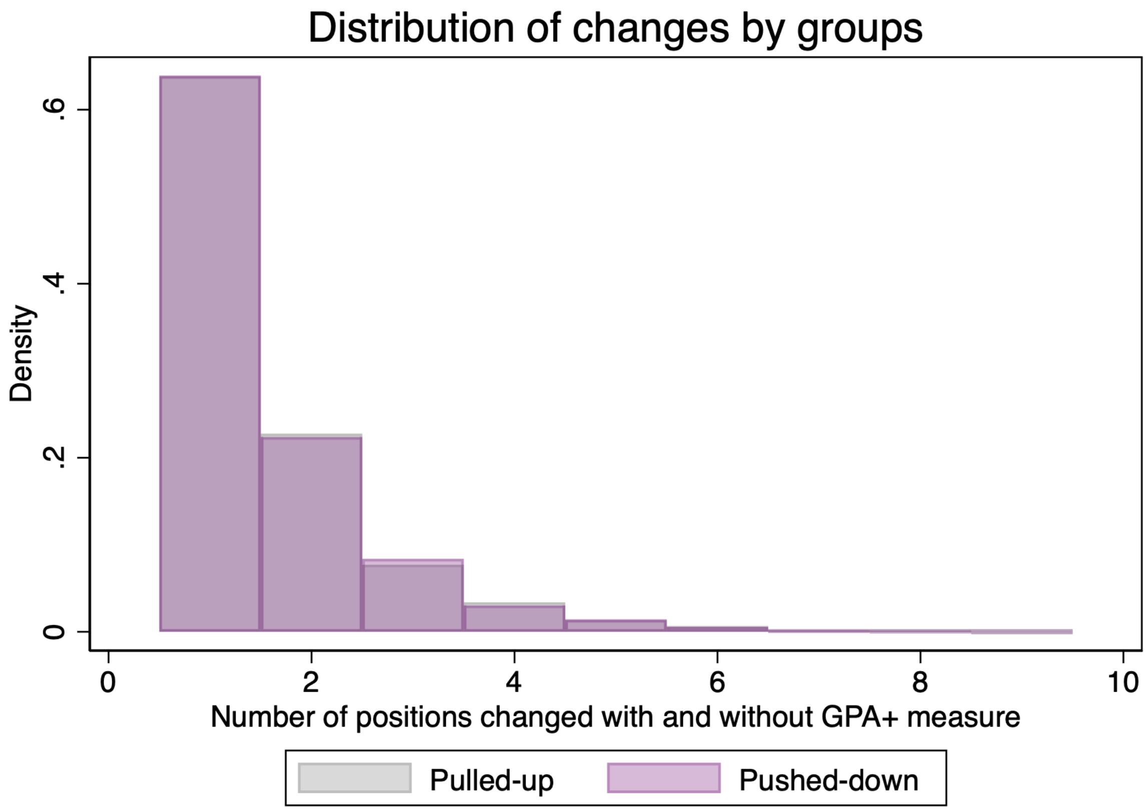
Notes: boost score for cohort 2011, 2012 and 2013. For 2013 GPA^{+} (and the inferred boost) was provided on the application data. For 2011 and 2012 boost was calculated according to the GPA^{+} formula using education records of the universe of high school students graduated between 2008 and 2012.

Figure 4



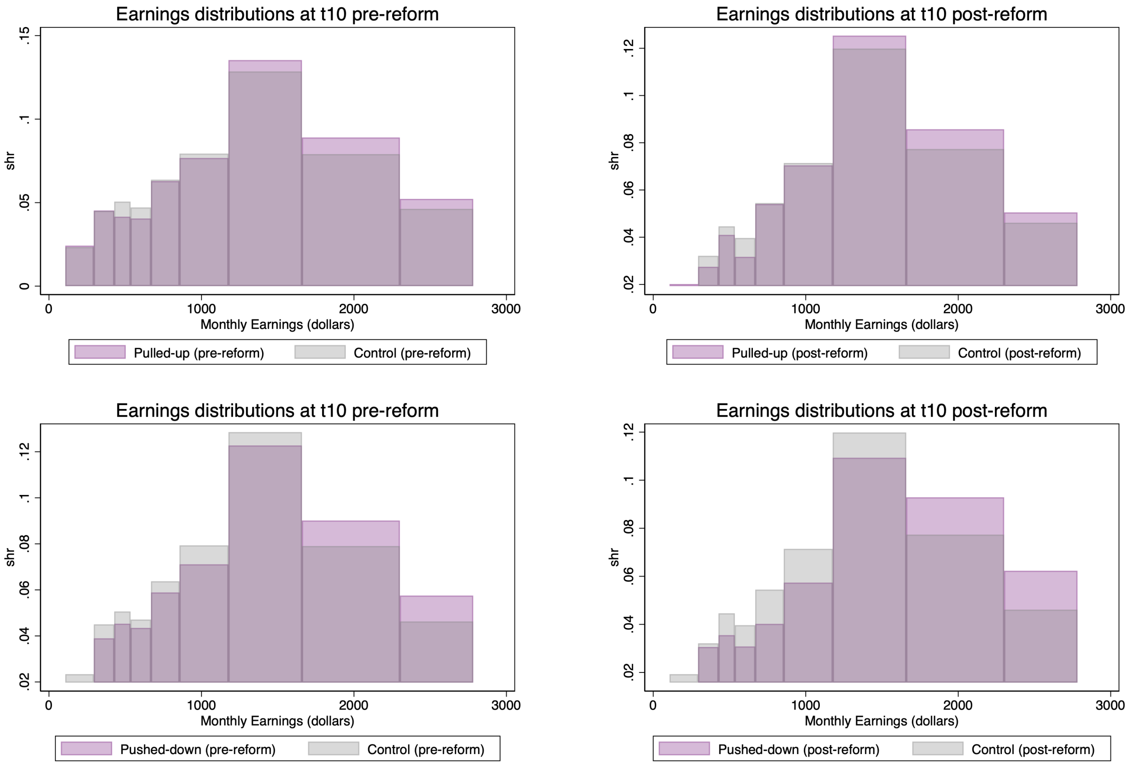
Notes: binscatter of the selectivity of the 1st preference by boost. Selectivity measure as the cutoff (application score of the last person admitted in the programs, measured pre-reform) of the program listed 1st. The x-axis have the GPA^{+} measure, but centered around the average score of the school. By centered at the school average we have that positive values correspond to the boost score.

Figure 5



Notes: distribution of pulled-up and pushed-down students based on the number of positions moved in their ranking between admission with and without GPA$^+$.

Figure 6: Earnings distribution



Notes: Earnings distribution for pulled-up and pushed-down groups, relative to unaffected, 10 years after application. Figures on the left show earnings distribution for students in cohort 2012 (pre-reform) and figures on the right show earnings distribution for students in cohort 2013 (post-reform).

Table 1: Summary Statistics for Groups of Interest

	Unaffected		Pulled-up		Pushed-down	
	2012	2013	2012	2013	2012	2013
N	108,167	109,440	3,753	4,515	4,416	4,253
Female (%)	53	52	62	60	41	40
Public School (%)	28	27	29	29	26	25
Voucher School (%)	53	54	60	60	47	47
Private School (%)	19	18	10	11	27	28
Family Inc ($/mo)	689	714	573	594	809	869
Father with HS (%)	67	67	64	61	74	75
Mother with HS (%)	73	73	69	70	78	79
Father with College (%)	26	26	20	19	34	35
Mother with College (%)	21	21	16	16	27	29
Capital City (%)	39	39	46	46	54	53
Std Math	0.68	0.65	0.74	0.65	1.05	1.13
Std Verbal	0.66	0.65	0.70	0.62	1.01	1.04
Std GPA	0.75	0.73	1.40	1.28	0.42	0.58
Boost score	21	22	60	57	6	8

Notes: This table shows the summary statistics for the groups of interest, the year before and after the reform.

Table 2: Distribution of students by ranking with and without GPA$^+$

With GPA$^+$ Ranking	Without GPA$^+$ 1	2	3	4	5	6	7	8	9	10	NA
1	48,434	1,166	415	139	59	31	16	2	7	0	397
%	0.44	0.26	0.09	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.09
2	1,149	19,404	530	187	72	36	12	5	2	3	262
%	0.27	0.18	0.12	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.06
3	347	590	10,500	240	113	23	11	5	3	2	202
%	0.08	0.14	0.10	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.04
4	124	184	279	4,303	96	50	18	6	0	1	92
%	0.03	0.04	0.07	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.02
5	37	72	124	101	2,288	47	22	5	5	1	58
%	0.01	0.02	0.03	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.01
6	397	28	36	46	59	1,158	21	13	5	1	45
%	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01
7	9	12	12	16	22	21	651	12	8	3	26
%	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01
8	2	3	10	5	8	7	14	338	5	4	11
%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	2	1	3	4	3	3	5	14	193	8	7
%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	1	1	0	5	0	1	3		2	123	5
%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NA	269	220	141	94	62	29	13	15	8	9	22,048
%	0.06	0.05	0.03	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.20

Notes: this table presents the number of students in 2013 with admission at different ranking of their rank order list with and without the GPA$^+$. Values on green correspond to pushed-down cases and values on blue correspond to pulled-up students. Column 1 - row 1 (and all the diagonal) shows the number of students that with admission in their top choice under both regimes, therefore, they are classify as unaffected. The percentage value under the total number of students represent the proportion of students in that treatment group that have that combination of rankings.

Table 3: Distribution of pulled-up students by fields with and without GPA$^+$

With GPA$^+$ Ranking	Without GPA$^+$ MedOdon	Health	Sci	Engi	Tech	Business	Art	SocSci	Law	Educ
MedOdon	126	54	7	10	2	2	0	3	4	1
Health	3	425	51	21	34	21	2	32	2	44
Sci	0	19	57	23	25	3	0	5	0	10
Engi	1	7	23	359	111	51	2	5	2	2
Tech	0	9	19	79	266	20	20	7	1	10
Business	0	1	12	19	29	224	3	8	3	6
Art	0	0	1	0	7	0	18	7	0	4
SocSci	0	8	8	3	17	32	15	200	18	47
Law	0	0	0	1	4	11	0	29	63	9
Educ	0	4	4	6	13	9	6	29	4	194

Notes: Total number of pulled-up student in 2013 in each field combination based on the field of the program that they get admitted with the GPA$^+$ and the field of the program that they get admitted without the GPA$^+$.

Table 4: Distribution of pushed-down students by fields with and without GPA$^+$

With GPA$^+$ Ranking	Without GPA$^+$ MedOdon	Health	Sci	Engi	Tech	Business	Art	SocSci	Law	Educ
MedOdon	126	54	7	10	2	2	0	3	4	1
Health	3	425	51	21	34	21	2	32	2	44
Sci	0	19	57	23	25	3	0	5	0	10
Engi	1	7	23	359	111	51	2	5	2	2
Tech	0	9	19	79	266	20	20	7	1	10
Business	0	1	12	19	29	224	3	8	3	6
Art	0	0	1	0	7	0	18	7	0	4
SocSci	0	8	8	3	17	32	15	200	18	47
Law	0	0	0	1	4	11	0	29	63	9
Educ	0	4	4	6	13	9	6	29	4	194

Notes: Total number of pushed-down student in each field combination based on the field of the program that they get admitted with the GPA$^+$ and the field of the program that they get admitted without the GPA$^+$.

Table 5: Difference-in-differences estimates for 2012 and 2011

	(1) Enroll	(2) Enroll	(3) Grad by 8yr	(4) Grad by 8yr
Pulled-Up	0.001	-0.015	0.006	-0.009
	(0.011)	(0.010)	(0.011)	(0.011)
Pushed-Down	-0.010	-0.002	0.007	0.005
	(0.009)	(0.009)	(0.011)	(0.010)
Observations	211,872	211,872	211,872	211,872
Controls		✓		✓

Robust standard errors in parentheses

Notes: columns 1 and 3 have the estimates from the difference-in-difference without controls and columns 2 and 4 have the estimates for the same outcomes but controlling by individual characteristics.

Table 6: Enrollment rates at admission program by groups, before and after the reform

Total	**Unaffected**	**Pulled-Up**	**Pushed-Down**
Enrollment Pre-Reform (2012)	0.80	0.83	0.91
Enrollment Reform (2013)	0.79	0.87	0.85
Difference	-0.01	0.04	-0.06

Program	**Unaffected**	**Pulled-Up**	**Pushed-Down**
Enrollment Pre-Reform (2012)	0.60	0.53	0.78
Enrollment Reform (2013)	0.62	0.75	0.66
Difference	0.02	0.22	-0.12

Non-selective	**Unaffected**	**Pulled-Up**	**Pushed-Down**
Enrollment Pre-Reform (2012)	0.13	0.12	0.08
Enrollment Reform (2013)	0.10	0.05	0.08
Difference	-0.03	-0.07	0.00

Notes: averages for a variable that indicates if the student choose to enroll in the admission assignment. The difference by group, between after and before the reform is shown in the 3rd row.

Table 7: Diff-in-diff estimates for enrollment

	(1) Enrollment	(2) Enrollment	(3) Non-Select	(4) Non-Select
Pulled-Up x after	0.199***	0.219***	-0.049***	-0.057***
	(0.011)	(0.010)	(0.007)	(0.007)
Pushed-Down x after	-0.136***	-0.167***	0.023***	0.039***
	(0.010)	(0.010)	(0.007)	(0.006)
Obs.	234,544	234,544	234,544	234,544
Controls		✓		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.000	0.000	0.008	0.048

Robust standard errors in parentheses

Notes: columns 1 and 2 have estimates when the outcome is enrollment at the admission program. Column 3 and 4 have estimates for an indicator if the student enroll in a non-selective program. Columns 2 and 4 control for standardized test scores, GPA, family income, region, type of high school and gender.

Table 8: Diff-in-diff estimates for enrollment: sample with some admission offer under both regimes

	(1) Enrollment	(2) Enrollment
P-Up x after	0.165***	0.175***
	(0.0113)	(0.0111)
P-Down x after	-0.0947***	-0.110***
	(0.00987)	(0.00965)
Obs.	186,734	186,734
Controls		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.000	0.000

Robust standard errors in parentheses

Notes: same specification than Table 7, but restricted to students with some admission offer under both regimes.

Table 9: Changes in peer characteristics at chosen programs

Program Charact.	Diff-in-Diff Pulled-up	Pushed-down	Pre-Reform ($\bar{x}$) Control	Pulled-up	Pushed-down
Math (std)	0.264***	-0.212***	1.104	1.262	1.272
	(0.008)	(0.007)	[0.610]	[0.603]	[0.611]
Verbal (std)	0.235***	-0.230***	1.114	1.240	1.261
	(0.008)	(0.008)	[0.567]	[0.537]	[0.530]
GPA (std)	0.280***	-0.288***	1.165	1.317	1.276
	(0.009)	(0.008)	[0.575]	[0.519]	[0.544]
Grad on time	0.044***	-0.040***	0.389	0.384	0.374
	(0.007)	(0.006)	[0.263]	[0.271]	[0.267]
E(grad time)	0.026	-0.065**	5.110	5.163	5.161
	(0.027)	(0.027)	[0.725]	[0.779]	[0.820]

Robust standard errors in parentheses. Standard deviation in square brackets.

Notes: Columns 1 and 2 show the results for the main diff-in-diff specification for the outcome 5 different outcomes: (i) average math score of students enrolled at the chosen program pre-reform, (ii) average verbal score of students enrolled at the chosen program pre-reform, (iii) average GPA score of the students enrolled at the chosen program pre-reform, (iv)probability of graduation on time by the students enrolled at the chosen program pre-reform, (v) expected graduation time based on the class structure at the chosen program. Columns 3-5 show the averages and standard deviation of these variables for the 3 groups of interest, pre-reform.

Table 10: Effect on enrollment by second year

	(1) Any	(2) Any	(3) Selective	(4) Selective
P-Up x after	0.0033	0.0181**	0.0410***	0.0643***
	(0.0079)	(0.0076)	(0.0098)	(0.0090)
P-Down x after	0.0128*	-0.0075	-0.0159*	-0.0521***
	(0.0071)	(0.0070)	(0.0091)	(0.0085)
Obs.	234,544	234,544	234,544	234,544
Controls		✓		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.141	0.315	0.066	0.338

Robust standard errors in parentheses

Notes: Columns 1 and 2 show the results for the main diff-in-diff specification using an indicator if the student is enroll at some program by second year. Columns 3 and 4 show the estimates for an indicator of enrollment in a selective program by second year.

Table 11: Effect on re-application by second year

	(1) Reapplication	(2) Reapplication
P-Up x after	-0.0387***	-0.0374***
	(0.0091)	(0.0091)
P-Down x after	0.0739***	0.0717***
	(0.0086)	(0.0086)
Obs.	234,544	234,544
Controls		✓

Robust standard errors in parentheses

Notes: diff-in-diff estimates using an indicator if the student participate on the application process on the second year.

Table 12: Effect on graduation from admission program

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.042***	0.072***	0.084***	0.043***
	(0.008)	(0.009)	(0.010)	(0.010)
P-Down x after	-0.033***	-0.060***	-0.082***	-0.039***
	(0.007)	(0.009)	(0.009)	(0.010)
Obs.	234,544	234,544	234,544	234,544
Controls	✓	✓	✓	✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.397	0.366	0.917	0.742

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 13: Effect on graduation from admission program conditional on some admission offer with both mechanism

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.037***	0.065***	0.078***	0.034***
	(0.009)	(0.011)	(0.011)	(0.012)
P-Down x after	-0.020**	-0.040***	-0.062***	-0.017
	(0.009)	(0.010)	(0.011)	(0.011)
Obs.	186,734	186,734	186,734	186,734
Controls	✓	✓	✓	✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.195	0.100	0.305	0.295

Robust standard errors in parentheses

Notes: Diff-in-diff results for the sample of students with some admission with and without the inclusion of the GPA$^+$ measure. Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admitted program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 14: Effect on graduation from admission program conditional on enrollment

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	-0.012	-0.009	-0.010	-0.000
	(0.012)	(0.013)	(0.014)	(0.014)
P-Down x after	-0.005	-0.018	-0.034***	0.001
	(0.010)	(0.012)	(0.012)	(0.012)
Obs.	144,540	144,540	144,540	144,540
Controls	✓	✓	✓	✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.302	0.126	0.020	0.989

Robust standard errors in parentheses

Notes: Diff-in-diff results for the sample of students that enroll in 1st year. Columns 1-3 show estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 15: Mismatch effect exercise

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.047***	0.078***	0.091***	0.049***
	(0.007)	(0.009)	(0.010)	(0.010)
Obs.	234,529	234,529	234,529	234,529
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: This table shows the effect on graduation from admission into a more selective program. The diff-in-diff specification controls by the admission program without the local context GPA reform in order to ensure that estimation uses only variation from students with admission to more selective programs after the reform, and not from potential changes in the compositions of admission programs between 2012 and 2013.

Table 16: Effect on STEM applicants

	(1) Admission	(2) Enrollment	(3) Enrollment	(4) Grad by 8yr	(5) Grad or enroll by 8 yr
P-Up x after	0.061***	0.216***	0.169***	0.061***	0.052***
	(0.010)	(0.014)	(0.015)	(0.014)	(0.016)
P-Down x after	-0.030***	-0.166***	-0.120***	-0.047***	-0.035**
	(0.010)	(0.013)	(0.012)	(0.014)	(0.016)
Obs.	234,544	110,791	97,350	97,350	97,350
Controls	✓	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: Column 1 shows the coefficient for the indicator of admission offer in STEM using the main diff-in-diff specification. Column 2 shows the effect on enrollment for STEM applicants. Column 3 restrict the sample of column 2 only to students that have some admission offer with and without GPA. Column 4 present the effects on graduation for the same sample than column 3. Finally, column 5 present the results conditional on enrollment.

Table 17: Graduation averages from any program by groups, before and after the reform

	Unaffected	Pulled-Up	Pushed-Down
Grad by 6yr Pre-Reform (2012)	0.22	0.24	0.21
Grad by 6yr Reform (2013)	0.21	0.22	0.19
Difference	-0.01	-0.02	-0.02

	Unaffected	Pulled-Up	Pushed-Down
Grad by 7yr Pre-Reform (2012)	0.36	0.40	0.35
Grad by 7yr Reform (2013)	0.34	0.37	0.34
Difference	-0.02	-0.03	-0.01

	Unaffected	Pulled-Up	Pushed-Down
Grad by 8yr Pre-Reform (2012)	0.46	0.51	0.47
Grad by 8yr Reform (2013)	0.42	0.45	0.42
Difference	-0.04	-0.06	-0.05

Notes: averages for a variable that indicates if the student graduates from some program (selective or non-selective). The difference by group, between after and before the reform is shown in the 3rd row.

Table 18: Effects on graduation from any program

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8 yr
P-Up x after	-0.003	0.005	-0.008	0.006
	(0.009)	(0.011)	(0.011)	(0.010)
P-Down x after	-0.012	-0.015	-0.032***	-0.006
	(0.009)	(0.010)	(0.011)	(0.010)
Obs.	234,544	234,544	234,544	234,544
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: diff-in-diff estimates for the indicator if the student graduate from some program by 6, 7 or 8 years. Column 4 show the results when the dependent variable takes the value of 1 if the student graduate or if the student is enrolled in some program 8 years after application.

Table 19: Effect on graduation from a selective program

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8yr
P-Up x after	0.019**	0.030***	0.019*	0.024**
	(0.009)	(0.010)	(0.011)	(0.010)
P-Down x after	-0.022***	-0.028***	-0.046***	-0.030***
	(0.008)	(0.010)	(0.010)	(0.010)
Obs.	234,544	234,544	234,544	234,544
Controls	✓	✓	✓	✓
	Selective	Selective	Selective	Selective

Robust standard errors in parentheses

Notes: Columns 1-3 show the results for graduation from a selective program by 6, 7 or 8 years after application. Columns 4-5 show the same results for non-selective programs.

Table 20: Effects on graduation from a non-selective program

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8yr
P-Up x after	-0.022***	-0.025***	-0.026***	-0.019***
	(0.004)	(0.005)	(0.005)	(0.006)
P-Down x after	0.009***	0.013***	0.014***	0.022***
	(0.004)	(0.004)	(0.004)	(0.005)
Obs.	234,544	234,544	234,544	234,544
Controls	✓		✓	✓
	Non-Selective	Non-Selective	Non-Selective	Non-Selective

Robust standard errors in parentheses

Notes: Columns 1-3 show the results for graduation from a selective program by 6, 7 or 8 years after application. Columns 4-5 show the same results for non-selective programs.

Table 21: Differential effect for students with big and small changes in selectivity

	(1) Enrollment	(2) Grad by 8yr	(3) Grad by 8yr	(4) Grad or enroll by 8 yr
Small Pulled-Up x after	0.195***	0.069***	-0.034**	0.005
	(0.015)	(0.016)	(0.017)	(0.015)
Big Pulled-Up x after	0.151***	0.080***	0.007	-0.003
	(0.016)	(0.016)	(0.017)	(0.015)
Small Pushed-Down x after	-0.108***	-0.040**	0.000	0.007
	(0.013)	(0.016)	(0.017)	(0.015)
Big Pushed-Down x after	-0.112***	-0.085***	-0.036**	-0.014
	(0.014)	(0.016)	(0.017)	(0.015)
Obs.	186,734	186,734	186,734	186,734
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: Based on how much the average test score of the peers (selectivity of the programs) changed between the simulated program and the admission program, the pulled-up and pushed-down groups are split into big and small changes in selectivity. The sample contains only students who have some admission offer in both regimes. Column 1 shows how the reform affected enrollment for the four subgroups. Column 2 shows the change in the probability of program completion. Column 3 shows the effects of graduating from any program 8 years after admission. Column 4 shows the effects of graduating or still being in school 8 years after application, which takes into account the fact that students in the selective system may switch programs, which will cause them to graduate from college later.

Table 22: Effects on sample of students moved only one or more positions in their ranking with and without GPA$^+$

	(1) Enrollment	(2) Grad by 8yr	(3) Enrollment	(4) Enrollment	(5) Grad by 8yr	(6) Grad by 8yr
P-Up x after	0.130***	0.050***	0.283***	0.231***	0.101***	0.105***
	(0.014)	(0.014)	(0.015)	(0.019)	(0.013)	(0.018)
P-Down x after	-0.084***	-0.043***	-0.211***	-0.114***	-0.088***	-0.051***
	(0.012)	(0.014)	(0.015)	(0.017)	(0.013)	(0.018)
Obs.	181,950	181,950	226,088	178,278	226,088	178,278
Controls	✓	✓	✓	✓	✓	✓
xmark	Moved 1	Moved 1	Moved more	Moved more + offer	Moved more	Moved more + offer

Robust standard errors in parentheses

Notes: Columns 1 and 2 show the effect on enrollment and graduation from the admission program when students are moved one position in their ranking between using GPA$^+$ and not using it in the assignment process. Columns 3 and 4 show the enrollment effect on the sample of students whose admission was moved more than 1 position in their ranking; column 4 restrict the sample only to student that had some admission offer under both regimes. Columns 5 and 6 show the effect on program completion for the same samples of column 3 and 4.

A Heterogeneity Analysis

Table 23: Heterogeneity: Effects on enrollment by gender, family income and boost

	(1) Enrollment	(2) Enrollment	(3) Enrollment
P-Up x after	0.193***	0.192***	0.080***
	(0.017)	(0.014)	(0.029)
P-Down x after	-0.148***	-0.145***	-0.148***
	(0.013)	(0.011)	(0.012)
P-Up x after x Characteristic	0.009	0.020	0.155***
	(0.022)	(0.021)	(0.031)
P-Down x after x Characteristic	0.027	0.033	0.012
	(0.020)	(0.022)	(0.020)
After x Characteristic	-0.005	-0.002	-0.023***
	(0.004)	(0.004)	(0.004)
Obs.	234,544	234,544	234,544
Controls	✓	✓	✓
Characteristic	Female	Low Income	Boost
PU Fraction	61%	45%	85%
PD Fraction	41%	30%	32%

Robust standard errors in parentheses

Notes: main diff-in-diff specification for enrollment fully interacted with (i) female indicator, (ii) low income indicator, and (iii) boost indicator.

Table 24: Heterogeneity: Effects on graduation from same program by gender, family income and boost

	(1) Grad by 8yr	(2) Grad by 8yr	(3) Grad by 8yr
P-Up x after	0.042***	0.082***	0.025
	(0.014)	(0.013)	(0.022)
P-Down x after	-0.051***	-0.058***	-0.055***
	(0.012)	(0.012)	(0.011)
P-Up x after x Characteristic	0.047**	-0.025	0.065***
	(0.019)	(0.020)	(0.025)
P-Down x after x Characteristic	-0.020	-0.013	-0.049**
	(0.020)	(0.021)	(0.021)
After x Characteristic	0.010***	0.006*	-0.015***
	(0.004)	(0.004)	(0.004)
Obs.	234,544	234,544	234,544
Controls	✓	✓	✓
Characteristic	Female	Low Income	Boost
PU Fraction	61%	45%	85%
PD Fraction	41%	30%	32%

Robust standard errors in parentheses

Notes: main diff-in-diff specification for graduation from assigned program fully interacted with (i) female indicator, (ii) low income indicator, and (iii) boost indicator.

Table 25: Heterogeneity: Effects on graduation from any program by gender, family income and boost

	(1) Grad by 8yr	(2) Grad by 8yr	(3) Grad by 8yr
P-Up x after	-0.023	-0.008	0.006
	(0.017)	(0.015)	(0.028)
P-Down x after	-0.004	-0.002	-0.008
	(0.014)	(0.013)	(0.013)
P-Up x after x Characteristic	0.003	-0.030	-0.018
	(0.023)	(0.023)	(0.031)
P-Down x after x Characteristic	-0.008	-0.026	-0.042*
	(0.022)	(0.024)	(0.023)
After x Characteristic	0.003	0.011***	-0.015***
	(0.004)	(0.004)	(0.004)
Obs.	234,544	234,544	234,544
Controls	✓	✓	✓
Characteristic	Female	Low Income	Boost
PU Fraction	61%	45%	85%
PD Fraction	41%	30%	32%

Robust standard errors in parentheses

Notes: main diff-in-diff specification for graduation from any program fully interacted with (i) female indicator, (ii) low income indicator, and (iii) boost indicator.

Table 26: Heterogeneity: Effects on graduation from a selective program by gender, family income and boost

	(1) Grad by 8yr	(2) Grad by 8yr	(3) Grad by 8yr
P-Up x after	-0.015	0.006	0.038
	(0.017)	(0.015)	(0.026)
P-Down x after	-0.006	-0.007	-0.022*
	(0.014)	(0.013)	(0.013)
P-Up x after x Characteristic	0.026	-0.010	-0.025
	(0.022)	(0.022)	(0.029)
P-Down x after x Characteristic	-0.022	-0.035	-0.031
	(0.022)	(0.023)	(0.023)
After x Characteristic	0.018***	0.021***	-0.021***
	(0.004)	(0.004)	(0.004)
Obs.	234,544	234,544	234,544
Controls	✓	✓	✓
Characteristic	Female	Low Income	Boost
PU Fraction	61%	45%	85%
PD Fraction	41%	30%	32%

Robust standard errors in parentheses

Notes: main diff-in-diff specification for graduation from a selective program fully interacted with (i) female indicator, (ii) low income indicator, and (iii) boost indicator.

Table 27: Heterogeneity: Effects on graduation or enroll after 8 years from a selective program by gender, family income and boost

	(1) Grad or enroll by 8 yr	(2) Grad or enroll by 8 yr	(3) Grad or enroll by 8 yr
P-Up x after	-0.015	-0.001	-0.030
	(0.017)	(0.013)	(0.029)
P-Down x after	0.028**	0.014	0.013
	(0.013)	(0.012)	(0.013)
P-Up x after x Characteristic	0.005	-0.021	0.037
	(0.021)	(0.021)	(0.031)
P-Down x after x Characteristic	-0.014	0.020	-0.013
	(0.020)	(0.022)	(0.020)
After x Characteristic	0.010**	0.013***	-0.007*
	(0.004)	(0.004)	(0.004)
Obs.	234,544	234,544	234,544
Controls	✓	✓	✓
Characteristic	Female	Low Income	Boost
PU Fraction	61%	45%	85%
PD Fraction	41%	30%	32%

Robust standard errors in parentheses

Notes: main diff-in-diff specification for graduation or enrollment after 8 year from a selective program fully interacted with (i) female indicator, (ii) low income indicator, and (iii) boost indicator.

B Main results from Section 3.4, boost sensitivity

Table 28: Diff-in-diff estimates for enrollment

	(1) Enrollment	(2) Enrollment	(3) Non-Select	(4) Non-Select
P-Up x after	0.197***	0.219***	-0.047***	-0.056***
	(0.011)	(0.011)	(0.007)	(0.007)
P-Down x after	-0.136***	-0.167***	0.023***	0.039***
	(0.010)	(0.010)	(0.006)	(0.006)
Obs.	233,789	233,789	233,789	233,789
Controls		✓		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.000	0.000	0.014	0.064

Robust standard errors in parentheses

Notes: columns 1 and 2 have estimates when the outcome is enrollment at the admission program. Column 3 and 4 have estimates for an indicator if the student enroll in a non-selective program. Columns 2 and 4 control for standardized test scores, GPA, family income, region, type of high school and gender.

Table 29: Diff-in-diff estimates for graduation from GPA^{+} program on sample without boost > 150

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.041***	0.070***	0.083***	0.041***
	(0.008)	(0.009)	(0.010)	(0.010)
P-Down x after	-0.033***	-0.060***	-0.082***	-0.038***
	(0.007)	(0.009)	(0.009)	(0.010)
Obs.	233,789	233,789	233,789	233,789
Controls	✓	✓	✓	✓
Test	0	0	0	0
p-value	0.483	0.418	0.968	0.852

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 30: Diff-in-diff estimates for any graduation on sample without boost > 150

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8 yr
P-Up x after	-0.005	0.005	-0.007	0.007
	(0.010)	(0.011)	(0.011)	(0.010)
P-Down x after	-0.012	-0.014	-0.032***	-0.006
	(0.009)	(0.010)	(0.011)	(0.010)
Obs.	233,789	233,789	233,789	233,789
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

C Main results from Section 3.4, long programs

Table 31: Diff-in-diff estimates for enrollment on sample without long programs

	(1) Enrollment	(2) Enrollment	(3) Non-Select	(4) Non-Select
P-Up x after	0.210***	0.238***	-0.067***	-0.078***
	(0.014)	(0.013)	(0.010)	(0.009)
P-Down x after	-0.141***	-0.177***	0.025***	0.043***
	(0.013)	(0.013)	(0.009)	(0.009)
Obs.	178,760	178,760	178,760	178,760
Controls		✓		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.000	0.001	0.002	0.009

Robust standard errors in parentheses

Notes: results for sample without students in programs with 6 or 7 expected year. Columns 1 and 2 have estimates when the outcome is enrollment at the admission program. Column 3 and 4 have estimates for an indicator if the student enroll in a non-selective program. Columns 2 and 4 control for standardized test scores, GPA, family income, region, type of high school and gender.

Table 32: Diff-in-diff estimates for graduation from GPA$^+$ program on sample without long programs

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.065***	0.084***	0.098***	0.061***
	(0.011)	(0.012)	(0.012)	(0.013)
P-Down x after	-0.051***	-0.077***	-0.087***	-0.061***
	(0.011)	(0.012)	(0.012)	(0.013)
Obs.	178,760	178,760	178,760	178,760
Controls	✓	✓	✓	✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.367	0.667	0.552	0.981

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 33: Diff-in-diff estimates for any graduation on sample without long programs

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8 yr
P-Up x after	0.008	0.007	0.008	0.009
	(0.013)	(0.014)	(0.014)	(0.013)
P-Down x after	-0.030**	-0.034**	-0.040***	-0.008
	(0.012)	(0.013)	(0.014)	(0.013)
Obs.	178,760	178,760	178,760	178,760
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

D Main results from Section 3.4, extra long programs

Table 34: Diff-in-diff estimates for enrollment on sample without extra long programs

	(1) Enrollment	(2) Enrollment	(3) Non-Select	(4) Non-Select
P-Up x after	0.195***	0.216***	-0.052***	-0.060***
	(0.011)	(0.011)	(0.007)	(0.007)
P-Down x after	-0.136***	-0.167***	0.023***	0.038***
	(0.010)	(0.010)	(0.007)	(0.006)
Obs.	228,741	228,741	228,741	228,741
Controls		✓		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.000	0.001	0.004	0.029

Robust standard errors in parentheses

Notes: results for sample without students in programs with 6 or 7 expected year. Columns 1 and 2 show estimates when the outcome is enrollment at the admission program. Column 3 and 4 have estimates for an indicator if the student enroll in a non-selective program. Columns 2 and 4 control for standardized test scores, GPA, family income, region, type of high school and gender.

Table 35: Diff-in-diff estimates for graduation from GPA^{+} program on sample without extra long programs

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.047***	0.066***	0.080***	0.042***
	(0.008)	(0.009)	(0.010)	(0.010)
P-Down x after	-0.034***	-0.055***	-0.072***	-0.035***
	(0.008)	(0.009)	(0.010)	(0.010)
Obs.	228,741	228,741	228,741	228,741
Controls	✓	✓	✓	✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.272	0.411	0.547	0.623

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 36: Diff-in-diff estimates for any graduation on sample without extra long programs

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8 yr
P-Up x after	0.002	0.001	-0.003	0.005
	(0.010)	(0.011)	(0.011)	(0.010)
P-Down x after	-0.014	-0.011	-0.023**	-0.005
	(0.009)	(0.010)	(0.011)	(0.010)
Obs.	228,741	228,741	228,741	228,741
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

E Main results from Section 3.4, Inference

Clustered standard errors at school-year level

Table 37: Diff-in-diff estimates for enrollment at admission program with school-year cluster standard errors

	(1) Enrollment	(2) Enrollment	(3) Non-Select	(4) Non-Select
P-Up x after	0.199***	0.219***	-0.049***	-0.057***
	(0.012)	(0.011)	(0.007)	(0.007)
P-Down x after	-0.136***	-0.167***	0.023***	0.039***
	(0.011)	(0.011)	(0.007)	(0.007)
Obs.	234,544	234,544	234,544	234,544
Controls		✓		✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.000	0.001	0.014	0.063

Robust standard errors in parentheses

Notes: Columns 1 and 2 show estimates when the outcome is enrollment at the admission program. Column 3 and 4 have estimates for an indicator if the student enroll in a non-selective program. Columns 2 and 4 control for standardized test scores, GPA, family income, region, type of high school and gender.

Table 38: Diff-in-diff estimates for graduation at admission program with school-year cluster standard errors

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad on time
P-Up x after	0.042***	0.072***	0.084***	0.043***
	(0.008)	(0.009)	(0.010)	(0.011)
P-Down x after	-0.033***	-0.060***	-0.082***	-0.039***
	(0.008)	(0.009)	(0.010)	(0.010)
Obs.	234,544	234,544	234,544	234,544
Controls	✓	✓	✓	✓
Test	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$	$\beta_3 = -\beta_4$
p-value	0.412	0.376	0.918	0.751

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 39: Diff-in-diff estimates for college graduation (any program) with school-year cluster standard errors

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad or enroll by 8 yr
P-Up x after	-0.003	0.005	-0.008	0.006
	(0.010)	(0.011)	(0.011)	(0.010)
P-Down x after	-0.012	-0.015	-0.032***	-0.006
	(0.009)	(0.010)	(0.011)	(0.010)
Obs.	234,544	234,544	234,544	234,544
Controls	✓	✓	✓	✓

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.

Table 40: Diff-in-diff estimates for graduation with school-year cluster standard errors

	(1) Grad by 6yr	(2) Grad by 7yr	(3) Grad by 8yr	(4) Grad by 6yr	(5) Grad by 7yr	(6) Grad by 8yr
P-Up x after	0.019**	0.030***	0.019*	-0.022***	-0.025***	-0.026***
	(0.009)	(0.011)	(0.011)	(0.004)	(0.005)	(0.005)
P-Down x after	-0.022***	-0.028***	-0.046***	0.009**	0.013***	0.014***
	(0.008)	(0.010)	(0.010)	(0.004)	(0.004)	(0.005)
Obs.	234,544	234,544	234,544	234,544	234,544	234,544
Controls	✓	✓	✓	✓		✓
	Selective	Selective	Selective	Non-Selective	Non-Selective	Non-Selective

Robust standard errors in parentheses

Notes: Columns 1-3 show diff-in-diff estimates for an indicator if the student graduate from the admission program by 6, 7 and 8 years after application. Column 4 show the results for the outcome of graduation on time.