Skill Measures, School Admissions, and Graduation*

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Abstract

This paper studies the effects of including a measure of cumulative assessment in the priority ordering of a centralized education system where the allocation of scarce seats follows a single high-stakes standardized exam score. We use data from Mexico City, where the most academically demanding high schools are over-subscribed and seat rationing relies solely on a admission exam score. We show that marginal admission to the most over-subscribed high schools decreases on-time graduation for students with low middle school GPAs and has no effect for students with high middle school GPAs. We then study the effects of counterfactual admission policies in which middle school GPA has increasing weight in the priority ordering. The larger the weight on GPA, the larger the share of girls and low-SES students matched to the most over-subscribed schools. However, the on-time graduation rates of these over-subscribed schools is concave with respect to the weight on GPA. The optimal admission policy would use both skill measures with a 60% weight on GPA and a 40% weight on the admission exam score.

Keywords: School choice, Upper-secondary education, Education policy, and Equality of opportunity in education.

JEL codes: I21, I24, I28, J24.

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1 Introduction

Centralized education systems that match students to public schools are expanding worldwide [Neilson, 2019]. Because schools have limited seats and many schools experience excess demand, centralized systems need a way to ration the available seats [Shi, 2022]. Since using prices as a rationing mechanism is not feasible for K-12 public schools, policymakers define priority orderings that solve the excess demand problem by defining who gets access to over-subscribed schools.[1]

Many centralized systems use the score in a single high-stakes standardized admission exam as their priority ordering.[2] Understanding the consequences of this practice is important for several reasons. First, performance on a single high-stakes standardized exam may be a noisy or incomplete measure of academic preparation. This could lead to a mismatch between students' preparation and some schools' academic requirements, affecting educational outcomes. Second, subpopulations with the same academic preparation may perform differently on high-stakes exams. This could lead to unequal access to highly demanded schools among well prepared students. For example, women and low-SES students tend to perform worse on high-stakes exams than men or high-SES students but have otherwise similar (or better) preparation under alternate measures [Azmat et al., 2016; Arenas et al., 2021].

In this paper, we explore mismatch and equity of access by studying the centralized high school admission system in Mexico City. In this system, students' priority ordering is solely based on their scores in a system-wide admission exam. We study the following question: Can on-time graduation and equity of access improve if the priority ordering also considers the information contained in GPAs? We focus on a measure of cumulative assesment (GPA), as a potential channel to improve student-school matches because previous literature shows that grades measure non-cognitive skills (e.g., effort and self-control) to a higher degree than achievement tests do, and that non-cognitive skills are important determinants

[1]Typical components of priority orderings are siblings, residential zones, lotteries, standardized exams, and GPAs.

[2]For example, the centralized systems in Romania, Kenya, Trinidad and Tobago, Ghana, Barbados, and Mexico City. In the US, selective schools in NYC rely solely on a standardized exam. In contrast, selective schools in Chicago and Boston combine standardized exams and GPA.

of desirable educational outcomes [Stinebrickner and Stinebrickner, 2006; Duckworth et al., 2012; Borghans et al., 2016; Jackson, 2018]. We use on-time graduation as our outcome of interest as it measures match quality with the admitted school.

We use all participants' administrative records in the centralized high school admission process in Mexico City. We complement the admission data by collecting official high school on-time graduation records (i.e., three years after admission) for all the students assigned to schools through the centralized admission process. This unique dataset features three advantages for the analysis. First, we have information on the application and on-time graduation of more than 250,000 students, allowing us to explore rich heterogeneity without running into statistical precision problems. Second, we observe strategy-proof measures of students' ranking of schools (i.e., students' ordinal preferences).[3] Third, our dataset includes applicants' skill measures beyond the admission exam score, such as their middle school GPA and score in a low-stakes standardized exam used for school accountability.

First, we shed light on the importance of the skills captured by GPA and their influence on students' probability of on-time graduation from the most over-subscribed and academically demanding schools in the system (i.e., elite schools). Using a Regression Discontinuity Design (RDD), we show that marginal admission to an elite school decreases the probability of on-time graduation by six percentage points. However, students at the margin of admission to an elite school are very heterogeneous in terms of their middle school GPAs. The correlation between the admission exam score and middle school GPA is 0.4. To study heterogeneity by GPA in the effect of interest, we implement RDDs separately for students with above- and below-median GPAs. We find that for students with below-median GPAs marginal admission to an elite school decreases the probability of on-time graduation by fourteen percentage points. For students with above-median GPAs, marginal admission to an elite school does not affect their probability of on-time graduation. That is, the effect of marginal admission to an elite school on on-time graduation depends on students having high or low GPAs.

[3]The matching algorithm is the Serial Dictatorship which is strategy-proof [Svensson, 1999] when there are no constraints in the length of the application lists. In Mexico City, students can only rank up to twenty schools, but this constraint is not binding as 97% of them submit shorter lists. In addition, students submit their application lists before they know their priority index. Uncertainty in the priority index incentivizes truthful revelation of preferences.

We also implement RDDs separately for boys and girls and find heterogeneous effects by gender. We find that the effect for boys is similar to the one for students with low GPAs, and the effect for girls is similar to that for students with high GPAs. Boys experience a decrease in their on-time graduation probability, while girls are unaffected. This is consistent with previous findings showing that school quality affects the educational attainment for boys and girls differently [Jackson, 2010; Clark, 2010; Deming et al., 2014]. We further show that a potential explanation behind these results is that girls have higher GPAs than boys at all levels of the admission exam score, including the elite schools admission cutoffs.

In terms of our research question, our first set of results imply that, even for students at the margin of admission to the most over-subscribed schools, an assignment mechanism that relies on a single measure of skills may affect educational outcomes if it excludes important information about a student's academic potential. In particular, if it excludes the information contained in grades. In addition, that there is scope for increasing equality of access without affecting the on-time graduation rate by giving students more credit for their higher grades.

Motivated by these results, we then define and study the effects of counterfactual admission policies that could increase equality of access and better match students to schools. We create a grid of weights based on the admission exam score and GPA, and for each combination of weights, we run the Serial Dictatorship algorithm to obtain counterfactual matches. We then estimate discrete choice on-time graduation models for each school in the baseline. We follow Dale and Krueger [2014] in that our on-time graduation models include controls for the characteristics of students' application lists to deal with commonly unobserved student preferences that could affect their on-time graduation. To calculate counterfactual on-time graduation rates, we combine the estimated parameters with the characteristics of the students allocated to each school in the counterfactuals. We proceed this way for three reasons. First, changes in the priority ordering affect students beyond the margin of admission to over-subscribed schools for whom our RDD estimates may not be informative. Second, we let our counterfactual policies consider students' preferences when creating new matches. Third, we capture our policies' general equilibrium effects since changes in the priority ordering could induce placement and displacement effects that affect even students who do not apply to over-subscribed schools.

There are two important findings from the counterfactual analysis. First, the higher the weight on GPA, the higher the share of girls and low-SES students matched to elite schools. We observe an increase in the share of girls because they have higher GPAs than boys and they also prefer elite schools than non-elite schools, so the counterfactuals provide them with greater access to their preferred schools. We observe an increase in the share of low-SES students because the admission exam score is highly correlated with family income, whereas GPA is not. Second, the on-time graduation rate from elite schools has a concave relationship with the weight on GPA. The concave relationship is a product of *both* the admission exam score and GPA being important determinants of on-time graduation even conditional on each other. For a central planner who is interested in equity in access and on-time graduation at elite schools, optimal weights on the admission exam score and GPA are 40% and 60%, respectively.

Our paper contributes to three strands of the literature. First, it contributes to the literature on centralized education systems. Most of the previous literature considers school priorities as given and studies the consequences of using different matching mechanisms to allocate students to schools [Pathak, 2011; Agarwal and Somaini, 2020]. Yet, defining a priority structure is an integral part of the design of a centralized system. Neilson [2019] reviews centralized education systems worldwide and highlights that the consequences of implementing different priority structures are understudied. Shi [2022] and Abdulkadiroğlu et al. [2021] are the closest papers to ours. Their focus is on finding optimal priority structures in centralized education systems. We complement their work by also looking at students' downstream outcomes, such as on-time graduation rates, which are crucial to assess the impact of mismatch within an assignment system.[4]

Second, we contribute to the extensive literature studying the effects of elite/selective schools on educational outcomes.[5] For the Mexican context, Dustan et al. [2017] finds similar results to us but excludes from their analysis the most oversubscribed schools in the system

[4]As Agarwal et al. [2020] and Larroucau and Rios [2020] highlight, it is essential to understand how assignment mechanisms perform when evaluated on outcomes of policymakers' concern beyond efficiency measures based on revealed preferences.

[5]See Clark [2010]; Jackson [2010]; Pop-Eleches and Urquiola [2013]; Abdulkadiroğlu et al. [2014]; Dobbie and Fryer Jr [2014]; Lucas and Mbiti [2014]; Abdulkadiroğlu, Angrist, Narita, Pathak and Zarate [2017]; Dustan et al. [2017]; Beuermann and Jackson [2022]; Angrist et al. [2023].

(i.e., schools requested as their first choice by around 50% of students). We complement their work in three ways. First, we include in our analysis the most oversubscribed schools in the system and rely on administrative on-time graduation records instead of a proxy for graduation. Second, we explore heterogeneous results by gender and their connection with the heterogeneity by GPA. Third, we show that including GPA in the priority ordering improves on-time graduation *and* increases equality of access.

Lastly, we contribute to the literature on using achievement tests and grades in admission policies. Arenas and Calsamiglia [2022] study the effects of a policy change that increased the weight in standardized exams relative to high school grades in a university admission index. The change decreased the share of females at selective degrees and affected the females who were likely to do better in college than the males who benefited from the change. We complement their work by showing that over-reliance on standardized exams also affects academically prepared, low-SES students. Bleemer [2021] shows that a grade-based top-percent policy for university admission in California promoted economic mobility without efficiency losses. Our paper complements this work by showing that combining grades with standardized exams can also have these positive effects at an earlier stage than university.

The remainder of the paper proceeds as follows. Section 2 describes the education system in Mexico City. Section 3 provides details about the administrative data we use for the analysis. Section 4 contains the first part of our analysis describing the implementation and results of our RDDs. Section 5 includes the definition of our counterfactuals, our graduation model, and our counterfactuals results. Section 6 concludes.

2 Education in Mexico City

The school system in Mexico has three levels: elementary, middle and high school. Elementary school is six years long, and middle and high school are three years each. The centralized high school education system in Mexico City encompasses the Federal District and 22 nearby urban municipalities in the State of Mexico. Most of the high school admission process participants are middle school students who reside in Mexico City and are in their last semester of middle school. Additional participants (less than 25%) attend middle

Table 1: Sub-systems in 2007

	Number of Schools	Seats	First in ROL	Admission Cut-Off
SUB 1	14	14.1%	48.5%	86.3
SUB 2	16	8.7%	14.5%	79.6
SUB 3	1	0.4%	0.7%	74.0
SUB 4	2	0.9%	0.5%	60.5
SUB 5	40	16.9%	6.1%	49.2
SUB 6	215	22.8%	16.1%	47.0
SUB 7	186	17.6%	7.7%	44.5
SUB 8	179	18.4%	5.8%	35.8
SUB 9	5	0.3%	0.2%	32.4
Total	658	100.0%	100.0%	45.0

NOTE: This table shows the aggregate supply, demand, and equilibrium cut-offs for the high school sub-systems in Mexico City. The fourth column shows the average admission cut-offs of the schools in a given sub-system.

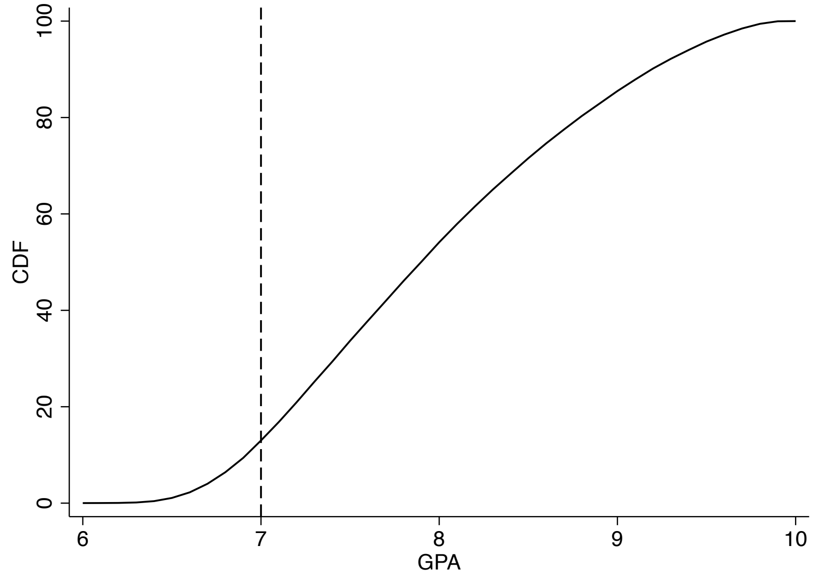
schools outside of Mexico City, already have a middle school certificate, or are enrolled in adult education. In total, about 300,000 students participate in the admission system.

Public high schools in Mexico City belong to one of nine sub-systems (Table 1). Each sub-system manages a different number of schools and offers its own curriculum. Two sub-systems, SUB 1 and SUB 2 in Table 1, enjoy a high reputation, are affiliated with the two most prestigious public universities in Mexico City, and offer a more advanced curriculum. For the rest of the paper, we refer to the schools belonging to these sub-systems as elite schools.

The first column of Table 1 shows the number of schools affiliated with each sub-system. The second column indicates that elite schools offer only 23% of the total number of seats in the system. The third column shows a high demand for elite schools; 63% of students list an elite school as their first option. Since elite schools are heavily over-subscribed, admission to elite schools is very competitive, which leads to these schools having high admission cut-off scores. We define an admission cut-off as the lowest score obtained by the students assigned to a given school in the previous admission cycle. The admission exam scores range from 31 to 128 points. The fourth column of Table 1 shows that elite schools' average admission cut-offs are the highest in the system.

The timeline of the application process is as follows. In February, students receive an information booklet describing the steps they need to follow. The information booklet also

Figure 1: Elite schools minimum GPA requirement



NOTE: This figure shows the cumulative distribution function of middle school GPA. The minimum GPA for middle school graduation and participation in the centralized high school admission system is six. To be considered for admission to an elite school, students must have a GPA greater or equal to seven (dashed line).

lists all available schools, their specializations, addresses, and previous years' admission cut-offs. The government also provides a website where students can download additional information about each school and use a mapping tool to see each school's location. In March, students submit a Rank Order List (ROL) listing up to 20 schools. In June, all students take a system-wide admission exam. We include a more detailed description of the admission exam in Appendix A.

All schools prioritize students based on the admission exam score. Elite schools exclude from consideration students with a middle school GPA lower than 7 out of 10. However, most of the students meet this requirement. To obtain a middle school certificate, students must have a GPA of at least 6 out of 10. In 2007, 90.62 percent of students met the GPA requirement for elite school admission (Figure 1).

Before implementing the matching algorithm, schools decide the number of seats to offer. During the matching process, some students may have the same admission exam score and compete for the last available seats at a given school. In this case, schools either admit or reject all tied students. For example, if a school has ten seats remaining during the matching process, but 20 tied students compete for them, the school must decide between admitting all 20 or rejecting them all.

The matching algorithm is the Serial Dictatorship. The Serial Dictatorship algorithm ranks students by the admission exam score and, proceeding in order, matches each applicant to her most preferred school among the schools with available seats. We provide a more detailed explanation of the Serial Dictatorship algorithm in Appendix B.

Some students may be left unmatched at the end of the matching process. There are two reasons why some students are unmatched. First, some students do not clear the cut-off for any schools they list in their ROLs. Second, some students only apply to elite schools and do not meet the minimum GPA requirement. Unmatched students can register at schools with available seats after the matching process is over.

3 Administrative Data

We use individual-level administrative data from the 2007 high school admission process in Mexico City. In that year, 256,335 students applied to 658 high schools. We observe each student's admission exam score, ROL, GPA, assigned school, and socio-demographic characteristics, such as gender and parental income. In Table 2, we include descriptive statistics of the applicant population. Students assigned to elite schools have higher admission exam scores, higher GPAs, and a larger share of them are male. The system-wide on-time graduation rate is 44%, and elite schools have an eleven percentage points higher average on-time graduation rate than non-elite schools. This difference likely reflects the selection of more skilled students into elite schools.

On the high school side, we have information on the number of seats each school offers, the sub-system to which each school belongs, and previous years' admission cut-offs for each school. With this information, we use the Serial Dictatorship algorithm and fully replicate the assignments we observe in the data (Table 3). Being able to reproduce the student-school matches observed in the data gives us confidence in the transparency of the admission system.

We collect administrative on-time graduation records from 2010, three years after admis-

Table 2: Students' characteristics by assignment group

	All	Elite	Non-Elite	Unmatched
Exam Score	65.24	90.16	60.27	51.20
	(19.21)	(10.87)	(14.88)	(12.80)
GPA	8.03	8.56	7.88	7.89
	(0.84)	(0.81)	(0.81)	(0.73)
Female	0.51	0.45	0.51	0.61
Age	15.82	15.56	15.90	15.88
	(1.60)	(1.23)	(1.72)	(1.55)
Length of ROL	9.32	9.62	9.53	8.03
	(3.75)	(3.92)	(3.71)	(3.41)
Position assigned	2.81	1.94	3.79	-
	(2.96)	(1.72)	(3.11)	-
On-time graduation	0.44	0.52	0.41	-
	256,335	54,654	162,063	39,618

NOTE: This table shows the characteristics of the middle school students participating in the assignment process. The length of ROL is the number of schools a student includes in her application list. The position assigned is where she ends up assigned in the ranking submitted by a student. On-time graduation indicates if a student graduated or not in three years. Standard deviations are in parenthesis.

Table 3: Matching outcomes in 2007

		N	%
Matched		216,717	73.02
Unmatched		39,618	13.35
Subtotal		256,335	
Ineligible	< 31 in exam	5,841	1.97
	No exam	6,353	2.14
	No middle school	28,249	9.52
Total		296,778	100

NOTE: This table shows the results of running the Serial Dictatorship algorithm using the administrative data. A student is ineligible if she obtains a score lower than 31 in the admission exam, does not show up for the exam, or does not obtain a middle school degree.

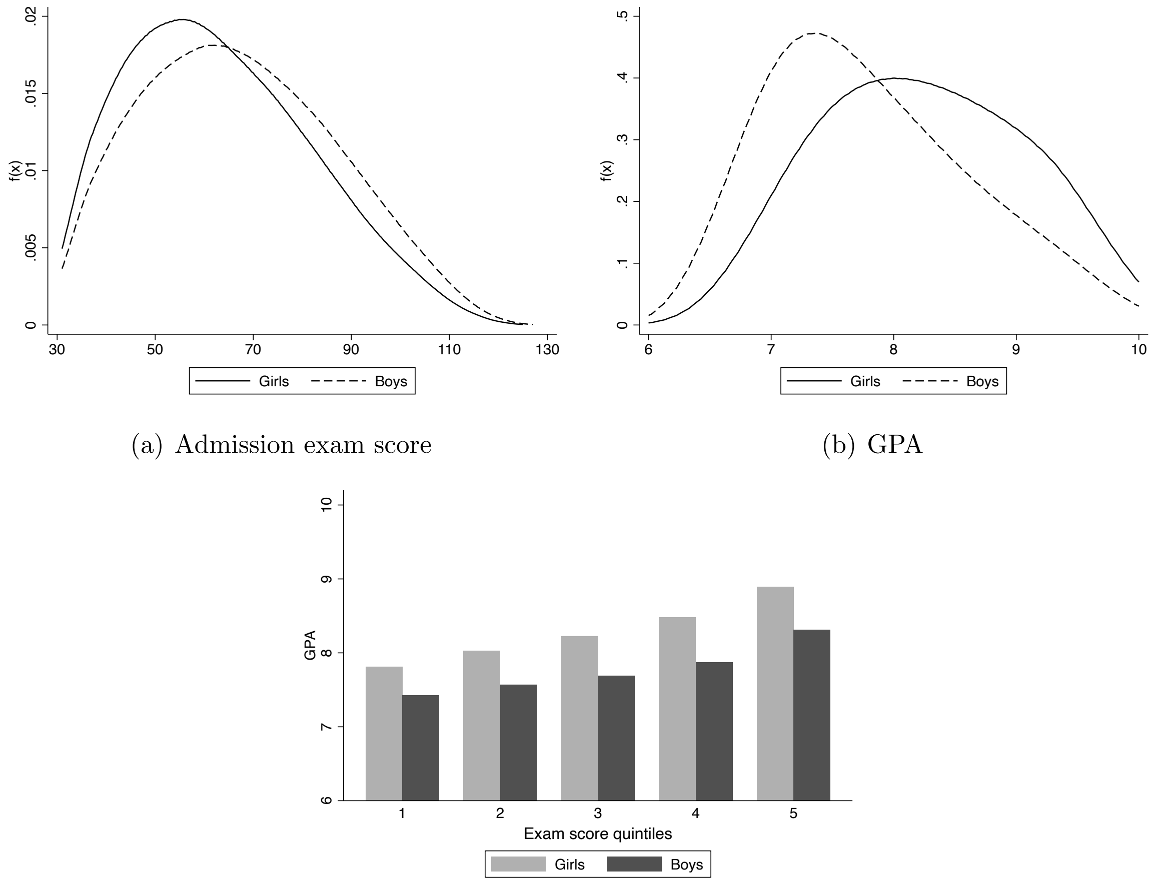
sion. The expected duration of high school is three years for all high schools. We obtained on-time graduation records for all the students assigned to eight of the nine sub-systems (80% of all the assigned students), including the two elite sub-systems. For the missing sub-system, we proxy for on-time graduation using students' participation in a standardized exam they took during the last semester of high school. This exam is low-stakes for the students and aims to track school level progress. Not all schools participate in this exam, but all schools in the missing sub-system do. To be consistent with our definition of on-time graduation, we rely on students' exam participation in 2010. We employ students' national identification numbers to merge the admissions data with our measures of on-time graduation.

Previous literature shows that females tend to perform worse in standardized tests than males [Niederle and Vesterlund, 2010]. This gap in performance does not mean that females have lower skills than males but that there are gender differences in performance under competitive pressure. In Figure 2, we show some descriptive statistics regarding gender differences in our available skill measures. Panel (a) shows that boys score higher than girls in the admission exam score. In contrast, Panel (b) shows that girls have higher GPAs than boys. Furthermore, Panel (c) shows that girls have higher GPAs than boys at every quintile of the admission exam score distribution. In this context, assigning students to elite schools based only on performance in an admission exam could limit girls' access to them. Further, if GPA is a strong predictor of on-time graduation, then such an admission rule could increase mismatch by restricting the access of high-GPA girls to the most academically demanding schools.

In addition to the admission and on-time graduation information, we observe each student's score on a standardized, low-stakes exam students take during the last semester of middle school. This exam is designed and implemented by the government for school accountability purposes. We refer to this exam as the low-stakes exam.

Our data collection efforts provide us with three advantages. First, we observe the application and on-time graduation records for a large number of students, which allows us to study heterogeneity in the causal effects of elite school admission. Second, due to the matching algorithm's properties and the admission process's timing, we observe strategy-proof measures of students' rankings of schools (i.e., their ordinal preferences). In the first part of the analysis, this allows us to compare the outcomes of students whose first best is gaining admission to an elite school and their second best is admission to a non-elite school. In the second part of the analysis, this allows us to control for commonly unobserved preference heterogeneity that affects the probability of on-time graduation. Third, having

Figure 2: Skill measures by gender



(a) Admission exam score

(b) GPA

(c) GPA and admission exam score

NOTE: Panel (a) in this figure shows the distribution of admission exam scores for girls and boys. Panel (b) in this figure shows the distribution of GPA for girls and boys. Panel (c) in this figure shows the average GPA for girls and boys at each quintile of the exam score.

information on GPA, the admission exam, and the additional low-stakes exam allows us to isolate what is measured by GPA from what is already taken into account by standardized exams throughout the analysis.

4 Regression Discontinuity Evidence

Elite schools are the most demanded schools in the system, and admission to them requires clearing their admission cut-offs. We exploit these cut-offs to identify the effect of marginal admission to an elite school on the probability of on-time graduation. We treat admission as equal to enrollment because enrollment at elite schools is almost universal. The average enrollment rate for students admitted to an elite school is 97.42%.

We follow Dustan et al. [2017] and construct a sample of students who would be assigned to an elite school if they meet the cut-off and assigned to a non-elite school otherwise. We impose three sample restrictions. First, we exclude all ineligible students for admission to an elite school. To be eligible for admission to an elite school, students must have a GPA higher than 7/10 during middle school. Second, we only include students who have applied to at least one elite and non-elite school. Third, we only include students who rank elite schools higher than non-elite ones. The purpose of the last restriction is to select students with similar preferences in that they prefer elite schools to non-elite schools.

Our strategy to estimate the effect of admission to a particular institution follows the same intuition as in Kirkeboen et al. [2016]. In our case, we consider only two institutions, elite and non-elite. In the estimation sample, we have students whose first best is an elite school and whose second best is a non-elite school in the local institution ranking (i.e., same ordinal preferences around their admission score). However, in addition to students having the same preferences in the local institution ranking, we only consider students who prefer elite to non-elite schools in their full ranking. We can impose this last restriction because most students who apply to both types of schools rank elite schools higher than non-elite schools. The previous restriction only excludes 815 (0.76%) students.

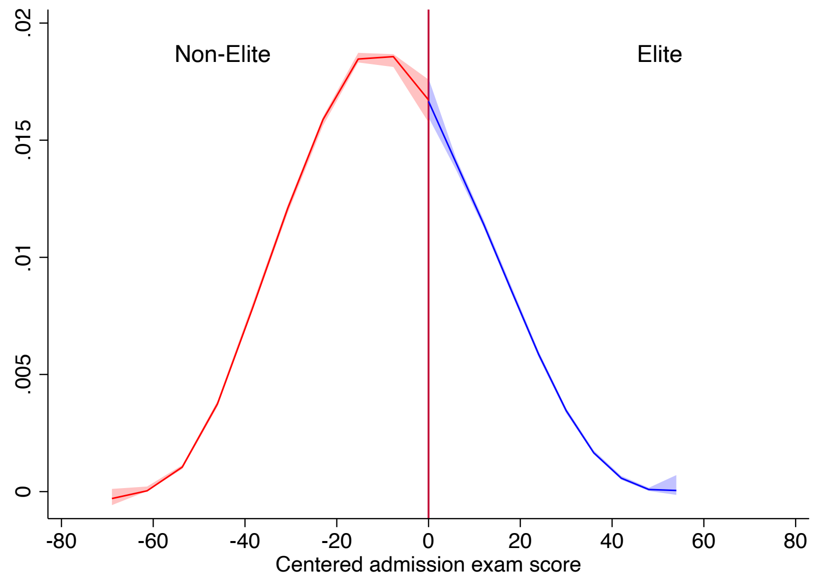
In our estimation sample, each student has a minimum cut-off for elite admission, c_k, that depends on her preferences. For example, if a student applied to multiple elite schools, her admission cut-off would be the lowest cut-off of the elite schools she included in her application. There are $k = 30$ groups of students that share the same c_k, corresponding to the cut-offs of the 30 elite schools. Within each group k, the following condition is satisfied:

$$\begin{cases} s_i \geqslant c_k \text{ admitted to some elite school,} \\ s_i < c_k \text{ admitted to some non-elite school,} \end{cases}$$

where s_i indicates student i score in the admission exam.

Our empirical specification follows Equation 1, where we stack our previously defined k groups. In this equation, y_{ik} is a dummy variable that denotes whether student i in group k

Figure 3: Continuity test



NOTE: This figure shows the density of the centered running variable. The shaded regions are 95% robust bias corrected confidence intervals.

graduates on time. We center the running variable s_i by the group-specific admission cut-offs c_k such that a positive value of $s_i - c_k$ indicates admission to an elite school. The dummy variable $admit_i$ takes a value of one when a student is admitted to an elite school and zero otherwise.

$$y_{ik} = \mu + \gamma admit_i + \delta(s_i - c_k) + \tau(s_i - c_k) \times admit_i + \epsilon_{ik}. \tag{1}$$

Our parameter of interest γ indicates the effect of marginal admission to an elite school on on-time graduation. For estimation, we follow the non-parametric robust estimator proposed by Calonico et al. [2014]. We also follow their method to calculate the mean squared error optimal bandwidth. For robustness, we also include additional results using half the optimal bandwidth, twice the optimal bandwidth, and polynomials of degrees two and three of the running variable (Appendix F).

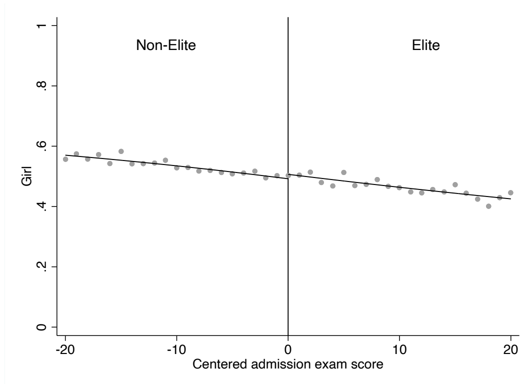
Regarding the validity of the design [Imbens and Lemieux, 2008], we show that there is no evidence of manipulation of the running variable around the admission cut-offs. If students could manipulate the running variable, they could sort themselves to be above an elite school admission cut-off. This type of sorting is unlikely in our context for two reasons. First, admission cut-offs are determined in equilibrium after students submit their applications and take the admission exam. Second, students do not know their score in the admission exam until the end of the admission process. If there were manipulation, we would expect to observe bunching of the running variable just above the admission cut-offs. Figure 3 shows the density of the running variable. The density does not show any bunching, and we do not reject its continuity at the admission cut-offs (T=-1.2). Our findings are consistent with the absence of manipulation.

Figure 4 shows that other predetermined covariates such as gender, age, GPA, family income, and number of siblings also do not vary discontinuously at the cut-offs. This is further evidence supporting the validity of the design. The estimates and standard errors are in Appendix C.

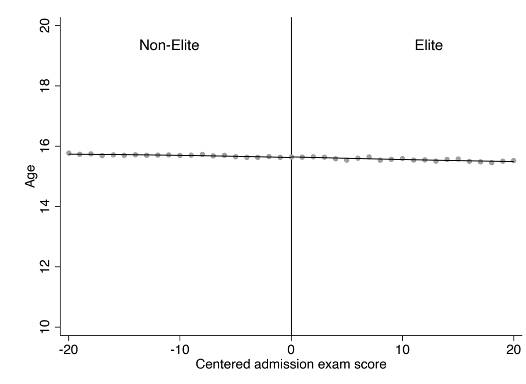
Figure 5 shows a graphical representation of the effect of marginal admission to an elite school on on-time graduation. Elite schools decrease the on-time graduation rate of marginally admitted students (six percentage points). We show the estimated parameter $\hat{\gamma}$ and its standard error in Appendix F. Elite schools have a more demanding curriculum, and students marginally admitted using a single standardized exam may not be prepared enough to complete their degree on time. However, this does not mean that all students marginally admitted experience a negative effect from elite schools. Since the correlation between the admission exam score and middle school GPA is 0.4, some students at the margin have high and low middle school GPAs. In the next section, we explore if the effects are different for these two subgroups of students.

Before we analyze the effect for students with high and low middle school GPAs, we show that the design is also valid for each subgroup. There is no evidence of manipulation of the running variable for our samples of high- and low-GPA students. In addition, the pre-determined covariates are also continuous at the cut-offs. We include these results in Appendixes D and E.

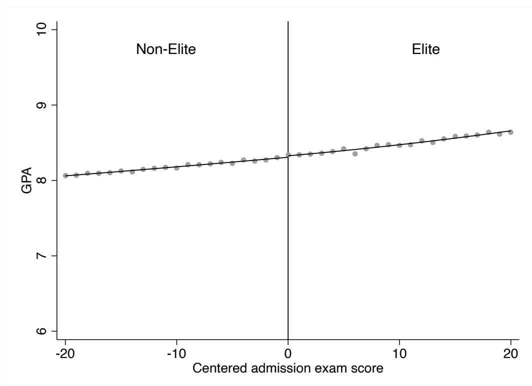
Figure 4: Predetermined covariates



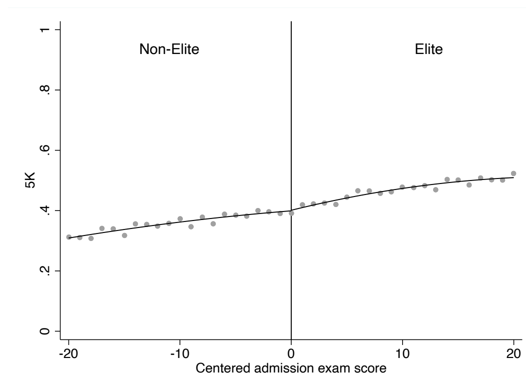
(a) Girl



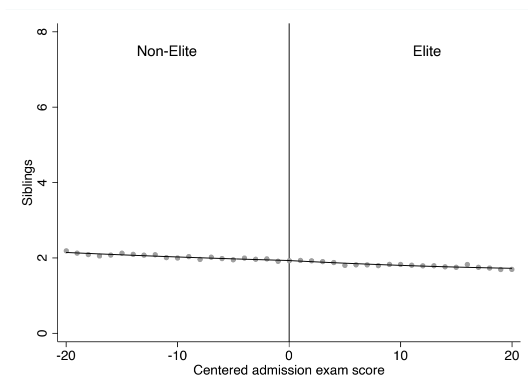
(b) Age



(c) GPA



(d) Income



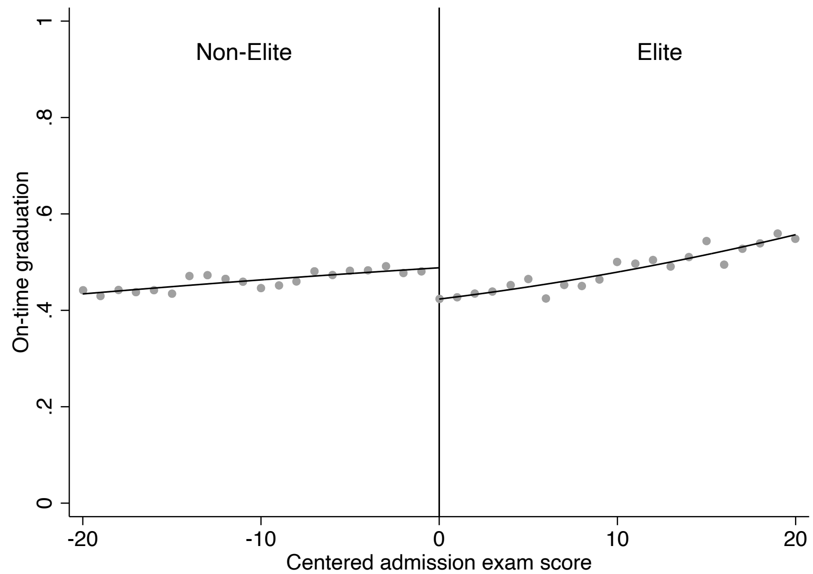
(e) Siblings

NOTE: This figure shows binned means of predetermined covariates around the elite admission thresholds. Income is a dummy variable indicating if the family monthly income is higher or lower that 5000 pesos (458 USD).

4.1 Heterogeneity by GPA

Students at the elite school admission cut-offs can be heterogeneous in other characteristics that affect on-time graduation. For example, they may have high or low GPAs. Borghans

Figure 5: The effect of elite schools on on-time graduation



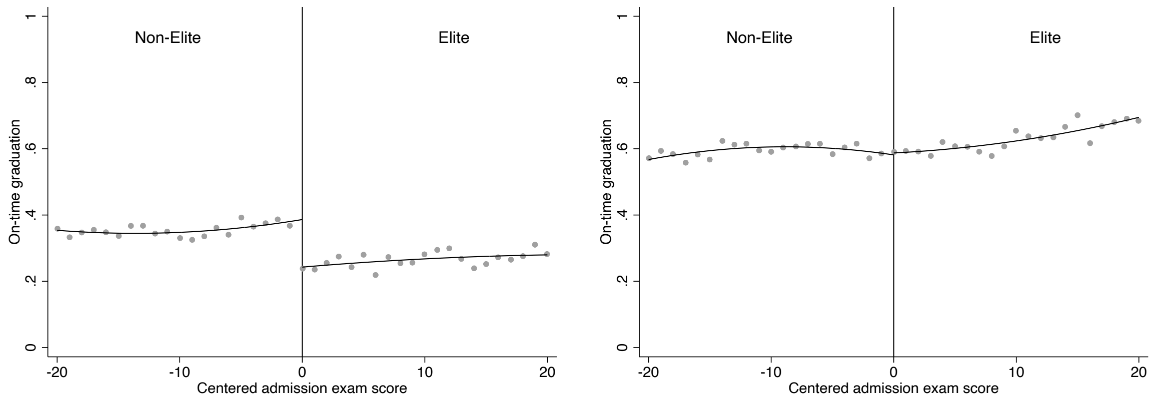
NOTE: This figure shows binned means of on-time graduation around the elite admission thresholds.

et al. [2016] show that grades and achievement tests capture IQ and personality traits, but grades weigh personality traits more heavily. Since personality traits such as self-control or conscientiousness could matter for elite school on-time graduation, we next explore if the effect is different for students with above and below-median GPAs.

In an extreme example, consider the case where the admission exam only captures IQ while GPA only captures self-control. Then, exploring our heterogeneity of interest would be equivalent to differentiating between the effect of elite schools on high-ability, low-self-control students and high-ability, high-self-control students. In this example, to gain admission to an elite school, a student needs to perform well in the admission exam (high-ability), but she need not have high self-control. To the extent that on-time graduation from an elite school requires you not only to have high ability but also have high self-control, we would expect differentiated effects.

The panels (a) and (b) in Figure 6 shows that the effect of marginal admission to an elite school on on-time graduation is heterogeneous by middle school GPA. It is negative (15 percentage points) and significant for students with below-median GPA and it does not affect the on-time graduation of students with above-median GPA. We include point estimates and standard errors in Appendix F. We take these results as evidence that on-time graduation

Figure 6: Elite school admission and on-time graduation by GPA



(a) Low middle school GPA (b) High middle school GPA

NOTE: This figure shows binned means of on-time graduation around the elite admission thresholds for students with high- and low-GPA.

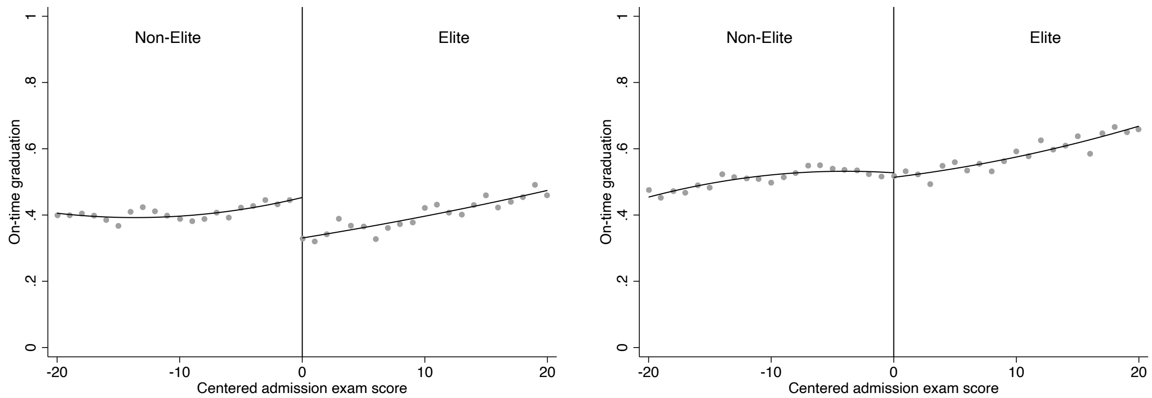
from elite schools require a combination of what is measured by the admission exam and the additional skills that GPA measures, when marginally admitted.

In Appendix I, instead of separating students as having above- or below-median GPAs in the entire distribution of GPAs, we define above- and below-median GPA students relative to the distribution of GPAs within their middle schools. We do this to control for middle school effects and ensure that our results are not driven by attending particular subgroups of middle schools. Our heterogeneous results by GPA are robust to this alternative definition of high and low GPA.

In Appendix J, we include an additional robustness check showing that the heterogeneity by GPA does not depend on elite schools having relatively higher or lower admission cut-offs. We separate elite schools into two groups, high- and low-cut-offs, among our thirty elite school cut-offs. We then show that the negative effect for low GPA students and the null effect for high GPA students is present in both groups of elite schools.

In Appendix G, we show that our heterogeneous results are not just the product of using multiple measures of the same skill (i.e., noise reduction). To do so, instead of GPA, we explore heterogeneity by performance in the low-stakes standardized exam. Our results in G shows negative effects on on-time graduation for both the high and low performers in the low-stakes standardized exam.

Figure 7: Elite school admission and on-time graduation by gender



(a) Boys (b) Girls

NOTE: This figure shows binned means of on-time graduation around the elite admission thresholds for boys and girls.

In Appendix H, to isolate the skills that GPA measures from those already accounted for by standardized exams, we use the residuals from regressing GPA on the admission exam score and the low-stakes standardized exam to define high and low GPA students. Our results show that our heterogeneous results in Figure 6 remain almost identical. We interpret this as evidence that the additional skills that GPA better captures are driving our heterogeneous results by GPA.

4.2 Heterogeneity by gender

In the last section, we showed that the effect of elite schools on the on-time graduation probability of marginally admitted students depends on their previous GPA. Since in Section 3, we showed that girls have higher GPAs than boys and, arguably, more of the skills needed to graduate on time from elite schools, we would also expect to observe heterogeneous effects by gender.

Figure 7 shows the results of implementing an RDD separately for girls and boys. The effect for boys is almost identical (decrease of 14 percentage points) to that for students with below-median GPA. In contrast, the effect for girls replicates the null effect for students with above-median GPA. We include point estimates and standard errors in Appendix F. Our results can partially be explained by differences in the skills that GPA measures between girls and boys.

To understand the source of heterogeneity in treatment effects, we follow Gerardino et al. [2017] and use propensity score weighting to keep one characteristic balanced while doing subgroup analysis for the other. In our case, we keep gender balanced while doing heterogeneity by GPA and keep GPA balanced while doing heterogeneity by gender. We show the main results of this exercise in Appendix K. When we hold gender balanced, we still observe heterogeneous results between high and low-GPA students, although the difference in effect sizes is smaller than before. However, when we hold GPA balanced, we no longer observe differences in the effect between girls and boys. We interpret this as evidence that what drives our heterogeneous results are the skills being captured by GPA, and what is behind the gender results is that girls have higher GPAs than boys at the elite admission cut-offs.

Overall, the results of our RDD analysis tell us two facts. First, marginal admission to elite schools only affects the on-time graduation for students without enough of the skills needed by their higher academic standards. Second, a combination of the admission exam and GPA is better at capturing these skills than the admission exam alone.

5 Counterfactual Admission Policies

Motivated by the RDD results, we examine the effects of counterfactual admission policies that may better match students to schools. Our admission policies combine the admission exam score and GPA to define new priority orderings. Consider a priority order that follows Equation 2. Since the matching algorithm is the Serial Dictatorship, all schools j follow the same priority for student i. Notice that when $w = 0$, we are in the baseline case where schools rank students using only their admission exam scores.

$$Priority_{ij}^{w} = (1 - w)EXAM_i + wGPA_i, \qquad (2)$$

where $w \in [0, 1]$.

We create a grid of weights w that go from zero to one in 0.1 increments for our counterfactuals. We run the Serial Dictatorship algorithm for each grid point to obtain the equilibrium allocation. Equation 3 defines f^{SD} as a matching function that has as inputs the priorities, the ROLs, and the offered seats. In our counterfactuals, we keep the $ROLs$ and $seats$ offered fixed while changing $Priority_{ij}^{w}$ through changes in w.

$$Match_{ij}^{w} = f^{SD}(Priority_{ij}^{w}, ROLs, seats). \tag{3}$$

We use GPA in levels in our main counterfactual analysis. However, depending on policymakers' concerns regarding possible undesirable behavioral responses to including the information in GPA, there are alternative ways to add this information to the priority order. For example, if policymakers' main concern is related to middle schools inflating grades as a response, then a better way to use the information in GPA would be to combine the admission exam score with within middle schools percentile ranking by GPA. Since within-school rankings are unaffected by grade inflation, such a policy could help prevent this response.

Another alternative is to use the low-stakes standardized exam to create a measure of GPA free of middle school effects. Policymakers can then combine the admission exam score with this measure to define the new priority ordering. The benefit of this option is that it removes middle schools' effects on GPA unrelated to a standardized measure of preparation. A limitation of this option is that by eliminating middle school fixed effects it may also be losing valuable information regarding a student's academic potential.

As we show in Appendix L and Appendix M, ex-ante, our counterfactual results are not sensitive to the implementation option. However, the best policy implementation will depend on policymakers' primary concerns. For example, in the Mexican context, where middle school mobility is more restricted since middle school admissions are also centralized [Fabregas, 2023], preventing grade inflation could be more important, and using within middle school percentile ranking by GPA could be the best implementation.

Students could also react by changing their efforts from time spent studying for the admission exam to time spent on their middle school coursework. Such a behavioral response is not necessarily negative. Suppose students move more of their effort towards coursework and away from studying for the entrance exam. In that case, we might expect on-time graduation rates to increase even more, assuming that studying for middle school coursework is more productive in building knowledge/skills associated with future academic success than studying for the entrance exam. In this case, we would expect our results to be a lower bound for the total effects on on-time graduation. Other potential ways to increase GPA, such as private tutoring, are less likely to occur given that we are considering a measure of overall GPA during three years of middle school.

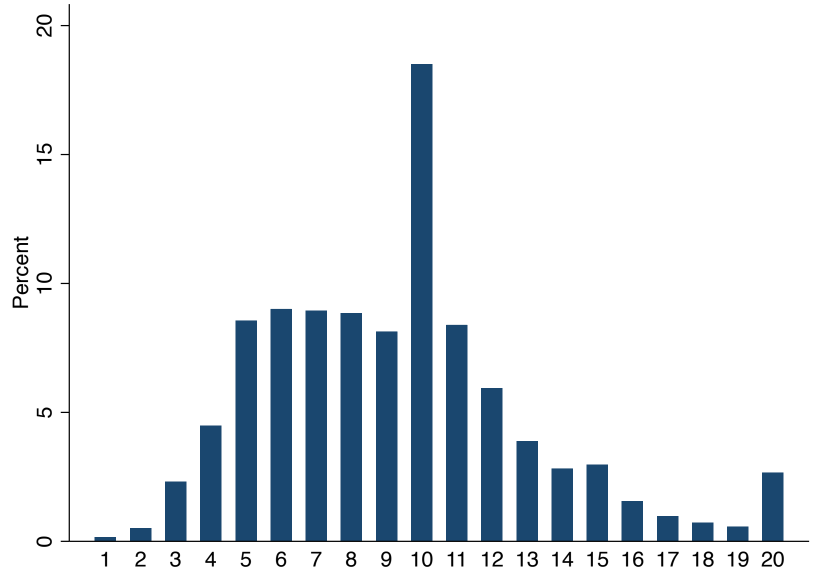
As highlighted in Equation 3, an important assumption we make when analyzing the effect of our counterfactual admission policies is that students' ROLs do not change when priorities change. There are some cases when the change in priorities could affect the observed ROLs. One case considers that students could be strategic when choosing their ROLs. In this case, the change in priorities would change students' ex-ante admission probabilities, and strategic students would consider the new admission probabilities and change their ROLs. In our context, we believe that students are unlikely to be strategic for two reasons.

First, the SD algorithm is strategy-proof when the length of students' ROLs is unrestricted [Haeringer and Klijn, 2009]. Although the Mexican system constrains the length of the ROLs to 20, only 2.7% of students submit a ROL of the maximum length. In Figure 8, we show the distribution of ROL lengths in our data. Since the constraint is not binding, the strategy-proof theoretical property likely holds in practice. That is, students truthfully report their preferences as their ROLs without considering admission probabilities.[6]

Second, another case where truth-telling may break even under a strategy-proof algorithm is the strict priority setting. Fack et al. [2019] consider this case. In the strict priority setting, students know their priority indices (e.g., admission exam scores) before choosing their ROLs. Consequently, students face limited uncertainty about their admission outcomes and may choose to omit schools for which they have zero ex-ante probability of admission. Students may be more uncertain about their admission outcomes if the priority index is unknown when

[6] Abdulkadiroğlu, Agarwal and Pathak [2017] impose a similar assumption when studying the centralized education system in New York City (NYC). The NYC system has around 400 high schools. Students can rank up to 12 schools. One of their arguments favoring truthful revelation of preferences is that in practice, only 20% of students rank 12 schools.

Figure 8: ROLs length



NOTE: This figure shows the distribution of ROLs length among the participants in the admission process.

they submit their ROLs. This is the case in Mexico City, where students submit their ROLs two months before taking the admission exam. The uncertainty in the priority index leads to admission probabilities that are rarely zero ex-ante and incentivizes truthful revelation of preferences.

Additionally, ROLs could change in the counterfactual if students' preferences depend on equilibrium outcomes. Consider the case where students' preferences for schools depend on the average skills of their future peers, and students have rational expectations. Then, the change in priorities could affect the average skills of students assigned to different schools, changing students' preferences for schools and their ROLs. A common assumption in the school choice literature is that preferences do not depend on equilibrium outcomes [Agarwal and Somaini, 2020]. We also work under this assumption. Importantly, even though some students get placed and displaced from different schools in the counterfactual, the changes in average students' skills (admission exam score combined with GPA) are small.

We estimate a flexible on-time graduation model to obtain a mapping between students' characteristics and their on-time graduation probability from a given school j (Equation 4). We then use our model parameters to map the counterfactual equilibrium allocations to on-time graduation rates. We proceed this way because our counterfactual admission policies affect some students for whom our RDD estimates may not be informative. For example, our RDD estimates may not be informative for students beyond the margin of admission to elite schools. In addition, they are not informative for the students placed and displaced from other types of schools due to the equilibrium effects induced by the policy changes.

$$P_j(x) = P_j[Y = 1 \mid X = x] = E_j[Y \mid X = x] \text{ , where } j \in \{1, ..., J\} \tag{4}$$

$$P_j(x) = G(\alpha_j + x'\beta_j). \tag{5}$$

We allow for school-specific model parameters, so individual-level characteristics can differentially affect on-time graduation probabilities from different schools (i.e., match effects). The dependent variable Y is a binary variable that equals one if student i graduated on time from a high school j, and zero if not. We divide the independent variables into three groups. The first group includes skill measurements such as the admission exam score and middle school GPA. The second group includes sociodemographics such as gender, age, and parental income. The third group includes characteristics of students' application lists. This last group of variables is motivated by the empirical specification in Dale and Krueger [2014], which takes advantage of the information revealed in college application lists. The characteristics of the application lists we include are the number of elite schools in students' ROLs, the length of their ROLs, and the average quality of the schools in their ROLs.[7]

Equation 5 denotes a mapping between student characteristics and the probability of graduation on time from school j. The mapping is defined by the parameters α_j, β_j, and the function G, which we assume to be the cumulative distribution function of the standard normal distribution. Under this assumption, our on-time graduation model is a probit for each school j.

Our counterfactuals assign some students to different schools than their initial assign-

[7] Our measures of quality are the schools' admission cutoffs in the previous year. The average quality of a ROL is the average of the previous year's schools' cutoffs listed in the ROL.

ment. For example, consider a student assigned to a school j in the baseline, which is assigned to a school j' in a counterfactual. To calculate her on-time graduation probability at the new school, we use the mapping from student characteristics to the on-time graduation probability we previously obtained for school j'. This student's counterfactual on-time graduation probability follows Equation 6.

$$\hat{P}_{j'}(x) = G(\hat{\alpha}_{j'} + x'\hat{\beta}_{j'}) \tag{6}$$

An implicit assumption in this exercise is that the parameters α_j and β_j do not change in the counterfactuals. Consider the case where these parameters capture fixed school characteristics such as infrastructure or quality of teachers. Then, the counterfactuals change the students' characteristics that interact with these attributes (i.e., match effects). A more complex case is when α_j and β_j also capture the effect of the average peer quality on a student's on-time graduation probability. Even under this case, our counterfactuals remains informative if the average peer quality at different schools does not change much. If we measure peer quality by a combination of the admission exam score and GPA, the changes in average peer quality are small. For example, in the counterfactual, students at elite schools have higher GPAs but lower admission exam scores.

We use school-level estimates for the counterfactuals, but for ease of exposition, we show estimates at the subsystem level in Table 4. The same as in Table 1, SUB 1 and SUB 2 are the two elite subsystems. We highlight two results from this table. First, the admission exam score and GPA are important determinants of on-time graduation in all subsystems. Second, GPA has the largest effect on on-time graduation at elite schools.

Table 4: Sub-system level estimates

	SUB 1	SUB 2	SUB 3	SUB 4	SUB 5	SUB 6	SUB 7	SUB 8	SUB 9
z-exam	0.019	0.051	0.028	0.137	0.095	0.090	0.053	0.086	0.022
	(0.006)	(0.007)	(0.036)	(0.023)	(0.004)	(0.003)	(0.004)	(0.004)	(0.026)
z-gpa	0.226	0.224	0.193	0.191	0.142	0.150	0.128	0.124	0.161
	(0.004)	(0.004)	(0.023)	(0.013)	(0.003)	(0.003)	(0.003)	(0.003)	(0.025)
Mean	0.531	0.509	0.543	0.379	0.301	0.537	0.388	0.364	0.488
N	33,762	20,892	882	2,077	34,384	51,190	39,245	33,586	699

NOTE: This table shows the marginal effects (at means) of probit on-time graduation models by sub-system. The admission exam score (z-exam) and GPA (z-gpa) are standardized to have a mean of zero and standard deviation of one. Each column includes the applicant's gender, age, parental income, and the characteristics of her ROL as additional regressors. SUB 1 and SUB 2 are the elite sub-systems. Standard errors in parenthesis.

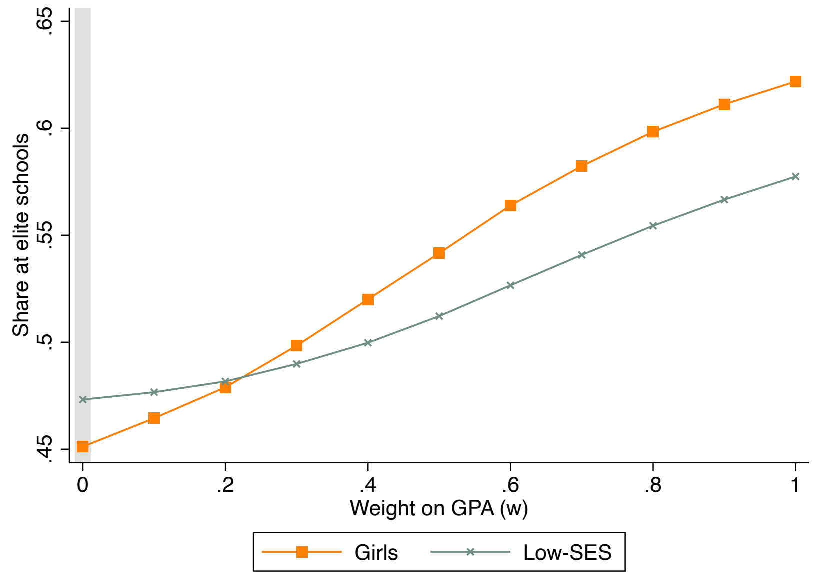
5.1 Results

Our counterfactual exercises result in different equilibrium allocations of students across schools. We first analyze the changes in the composition of students allocated to elite schools and then explore how these changes affect the on-time graduation rates at elite and non-elite schools.

Figure 9 shows that the higher the weight in GPA, the higher the share of low-SES students assigned to elite schools. Income is highly correlated with the admission exam score but less correlated with GPA. The correlation between income and the admission exam score can partially be explained by high-SES students accessing costly private exam preparation institutions. Adding weight to GPA makes the admission exam score relatively less important and increases low-SES students' access to elite schools. Both low- and high-SES students demand elite schools, but low-SES students have less access to them in the baseline.

Figure 9 also shows that the higher the weight in GPA, the higher the share of girls assigned to elite schools. This change occurs because girls list elite schools in their ROLs, but the current admission policy limits their access. By adding weight to GPA, a measure

Figure 9: Composition of students at elite schools



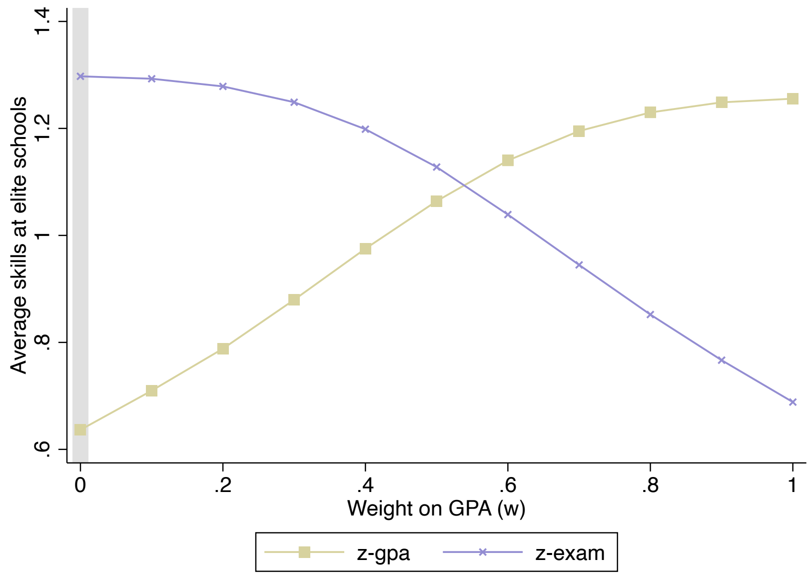
Note: This figure shows the share of girls and low-SES students admitted to elite schools in each counterfactual equilibrium associated with a combination of weights on GPA and the admission exam score. The x-axis indicates the weight on GPA (w). The weight on the admission exam score is $(1 - w)$. We define a low-SES student as one whose family income is lower than 5000 Mexican pesos per month (458 USD).

in which girls outperform boys (Figure 2), more girls gain access to elite schools.

Next, we explore changes in the composition of skills in elite schools. In Figure 10, we show that as we increase the weight on GPA (relative to the admission exam score), the average GPA of students at elite schools increases. In contrast, the average admission exam score decreases. Interestingly, as we increase the weight on GPA, the average admission score of elite school students decreases at a higher rate. Because the correlation between the admission exam score and GPA is low, as the weight on GPA increases, an increasing number of students with lower admission exam score gain access to elite schools.

In Figure 11, we show that the relationship between on-time graduation from an elite school and the weight on GPA have a concave relationship. Since the admission exam score and GPA are important determinants of on-time graduation from elite schools, the pattern of changes in skills composition in Figure 10 implies that it is not necessarily optimal to put all the weight on GPA. When the weight on GPA is too high, too many low admission exam

Figure 10: Skills of students at elite schools



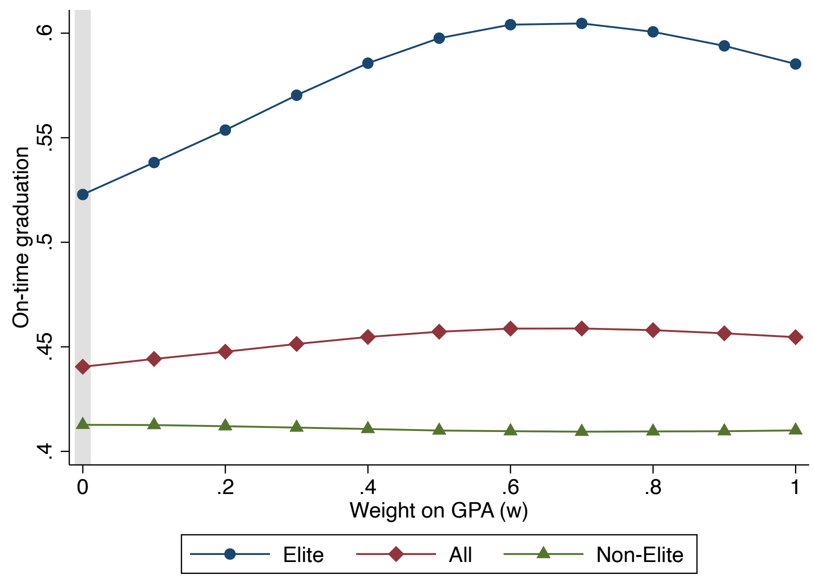
Note: This figure shows the average standardized admission exam score and GPA of students admitted to elite schools in each counterfactual equilibrium associated with a combination of weights on GPA and the admission exam score. The x-axis indicates the weight on GPA (w). The weight on the admission exam score is $(1 - w)$.

score students gain admission to elite schools, affecting the on-time graduation rate. Larger changes in on-time graduation occur at elite schools because they are the most affected by changes to the priority index, since most seat rationing applies to them. As we increase the weight on GPA, the on-time graduation for non-elite schools is mostly unaffected, while the overall on-time graduation in the system slightly increases.

Focusing on the on-time graduation rate at elite schools, in Figure 12, we show that girls' and low-SES students' on-time graduation rates also have a concave relationship with the weight on GPA. The on-time graduation rate for both groups of students reaches its maximum when the weight on GPA and the admission exam score are equal.

Overall, our counterfactuals give us insight into the optimal weights in skill measures. For example, consider that policymakers' objectives are to increase the share of low-SES students at elite schools, the share of females at elite schools, and maximize the elite schools' on-time graduation rate. In this case, the optimal weights are 60% on GPA and 40% on the admission exam score. However, if the objectives are to maximize the on-time graduation

Figure 11: On-time graduation



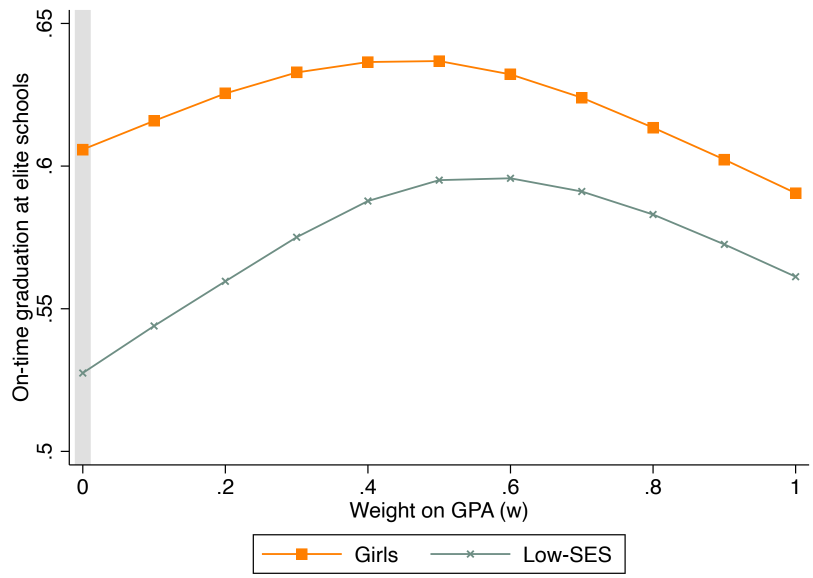
Note: This figure shows the average on-time graduation rate for each counterfactual equilibrium associated with a combination of weights on GPA and the admission exam score. We include this average for three groups of schools: elite, non-elite, and all. We define on-time graduation as graduating three years after admission, which reflects normal grade progression during high school. The x-axis indicates the weight on GPA (w). The weight on the admission exam score is $(1 - w)$.

rate of girls and low-SES students at elite schools, the optimal policy would put equal weight on both skill measures.

6 Conclusions

How a central planner chooses to ration school seats in a centralized education system can affect the equity of access and the on-time graduation rates. The relevance of this choice is highlighted when a system priority ordering includes skill measures, and students have diverse latent skills. In this case, a given priority ordering could match underprepared students with the most academically demanding schools, affecting their on-time graduation rate. Furthermore, priority orderings play an essential role when centralized education systems evaluations go beyond efficiency measures based on revealed preferences and consider additional policy-relevant outcomes such as equity of access and on-time graduation rates.

Figure 12: On-time graduation at elite schools



NOTE: This figure shows the average on-time graduation rate at elite schools for each counterfactual equilibrium associated with a combination of weights on GPA and the admission exam score. We include this average for two groups of students: girls and low-SES. We define on-time graduation as graduating three years after admission, which reflects normal grade progression during high school. The x-axis indicates the weight on GPA (w). The weight on the admission exam score is $(1 - w)$. We define a low-SES student as one whose monthly family income is lower than 5000 Mexican pesos (458 USD).

We use administrative data from the centralized high school admission system in Mexico City, where all schools share a priority ordering that relies solely on a standardized admission exam. We study the effects of adding the information in middle school GPA to the priority ordering. We focus on GPA because previous literature shows that grades measure non-cognitive skills to a higher degree than achievement tests and that non-cognitive skills are a strong predictor of educational success. We first show that students marginally admitted to academically elite schools in this system experience a decrease in their on-time graduation probability when they have a low middle school GPA and are unaffected when they have a high middle school GPA. Our first set of results motivates the importance of using the informational content of grades when considering how to admit students to schools.

Guided by these results, we then study the effects of counterfactual admission policies where the central planner increasingly adds weight to GPA in the priority order. We have two important findings. First, the higher the weight on GPA, the higher the share of girls and low-SES students admitted to elite schools. Behind this result is that girls have higher GPAs than boys, and income is less correlated with GPA than the admission exam score. Second, the on-time graduation rate at elite schools has a concave relationship with the weight on GPA. When the weight on GPA is too high, too many low admission exam score students gain access to elite schools, affecting the on-time graduation rate. Both GPA and admission exam score are important determinants of on-time graduation from elite schools. For a central planner that values equality of access and increasing the on-time graduation rate at elite schools, the optimal weights for GPA and the admission exam score are 60% and 40%, respectively.

A limitation of our study is that our counterfactual admission policies could induce behavioral responses that we are not currently considering. For example, they could affect students' effort allocation between exam preparation and middle school coursework by increasing the effort allocated to coursework. In this paper, we assume that study effort does not change. However, if increased study effort in middle school coursework leads to higher study effort in high school coursework and time spent studying for coursework is more productive than time spent studying for an admission exam, then our effect on the elite schools' on-time graduation rate would be a lower-bound.[8] As we also show in this paper, depending on their concerns regarding potential unintended responses, policymakers could flexibly choose how to incorporate the information contained in GPA in a priority ordering.

From a policy perspective, our results indicate that combining the informational content of GPA and the admission exam score in its priority ordering can benefit the centralized system in Mexico City. More broadly, other centralized systems that rely on a unique standardized exam to define school priorities could also benefit from adding some weight to GPA. Examples of such systems are the centralized education systems in Romania, Kenya, Trinidad and Tobago, Ghana, Barbados, and the college admission system in China.

[8]Stinebrickner and Stinebrickner [2006] show that coursework study effort is strongly correlated across time between high school and college.

References

Abdulkadiroğlu, A., Agarwal, N. and Pathak, P. A. [2017], 'The welfare effects of coordinated assignment: Evidence from the new york city high school match', *American Economic Review* **107**(12), 3635–89.

Abdulkadiroğlu, A., Angrist, J., Narita, Y., Pathak, P. and Zarate, R. [2017], 'Regression discontinuity in serial dictatorship: Achievement effects at chicago's exam schools', *American Economic Review, Papers and Proceedings* **107**(5), 240–245.

Abdulkadiroğlu, A., Angrist, J. and Pathak, P. [2014], 'The elite illusion: Achievement effects at boston and new york exam schools', *Econometrica* **82**(1), 137–196.

Abdulkadiroğlu, A., Dur, U. M. and Grigoryan, A. [2021], School assignment by match quality, Technical report, National Bureau of Economic Research.

Agarwal, N., Hodgson, C. and Somaini, P. [2020], Choices and outcomes in assignment mechanisms: The allocation of deceased donor kidneys, Technical report, National Bureau of Economic Research.

Agarwal, N. and Somaini, P. [2020], 'Revealed preference analysis of school choice models', *Annual Review of Economics* **12**, 471–501.

Angrist, J. D., Pathak, P. A. and Zarate, R. A. [2023], 'Choice and consequence: Assessing mismatch at chicago exam schools', *Journal of Public Economics* **223**, 104892.

Arenas, A. and Calsamiglia, C. [2022], Gender differences in high-stakes performance and college admission policies, Technical report, IZA Discussion Papers.

Arenas, A., Calsamiglia, C. and Loviglio, A. [2021], 'What is at stake without high-stakes exams? students' evaluation and admission to college at the time of covid-19', *Economics of education review* **83**, 102143.

Azmat, G., Calsamiglia, C. and Iriberri, N. [2016], 'Gender differences in response to big stakes', *Journal of the European Economic Association* **14**(6), 1372–1400.

Beuermann, D. W. and Jackson, C. K. [2022], 'The short-and long-run effects of attending the schools that parents prefer', *Journal of Human Resources* **57**(3), 725–746.

Bleemer, Z. [2021], Top percent policies and the return to postsecondary selectivity, *in* 'Top Percent Policies and the Return to Postsecondary Selectivity: Bleemer, Zachary', [Sl]: SSRN.

Borghans, L., Golsteyn, B. H., Heckman, J. J. and Humphries, J. E. [2016], 'What grades and achievement tests measure', *Proceedings of the National Academy of Sciences* **113**(47), 13354–13359.

Calonico, S., Cattaneo, M. D. and Titiunik, R. [2014], 'Robust nonparametric confidence intervals for regression-discontinuity designs', *Econometrica* **82**(6), 2295–2326.

Clark, D. [2010], 'Selective schools and academic achievement', *The BE Journal of Economic Analysis & Policy* **10**(1).

Dale, S. B. and Krueger, A. B. [2014], 'Estimating the effects of college characteristics over the career using administrative earnings data', *Journal of human resources* **49**(2), 323–358.

Deming, D. J., Hastings, J. S., Kane, T. J. and Staiger, D. O. [2014], 'School choice, school quality, and postsecondary attainment', *American Economic Review* **104**(3), 991–1013.

Dobbie, W. and Fryer Jr, R. G. [2014], 'The impact of attending a school with high-achieving peers: Evidence from the new york city exam schools', *American Economic Journal: Applied Economics* **6**(3), 58–75.

Duckworth, A. L., Quinn, P. D. and Tsukayama, E. [2012], 'What no child left behind leaves behind: The roles of iq and self-control in predicting standardized achievement test scores and report card grades.', *Journal of educational psychology* **104**(2), 439.

Dustan, A., De Janvry, A. and Sadoulet, E. [2017], 'Flourish or fail? the risky reward of elite high school admission in mexico city', *Journal of Human Resources* **52**(3), 756–799.

Fabregas, R. [2023], 'Trade-offs of attending better schools: Achievement, self-perceptions and educational trajectories', *The Economic Journal* p. uead042.

Fack, G., Grenet, J. and He, Y. [2019], 'Beyond truth-telling: Preference estimation with centralized school choice and college admissions', *American Economic Review* **109**(4), 1486–1529.

Gerardino, M. P., Litschig, S. and Pomeranz, D. [2017], 'Can audits backfire? evidence from public procurement in chile', *NBER Working Papers* (23978).

Haeringer, G. and Klijn, F. [2009], 'Constrained school choice', *Journal of Economic theory* **144**(5), 1921–1947.

Imbens, G. W. and Lemieux, T. [2008], 'Regression discontinuity designs: A guide to practice', *Journal of econometrics* **142**(2), 615–635.

Jackson, C. K. [2010], 'Do students benefit from attending better schools? evidence from rule-based student assignments in trinidad and tobago', *The Economic Journal* **120**(549), 1399–1429.

Jackson, C. K. [2018], 'What do test scores miss? the importance of teacher effects on non–test score outcomes', *Journal of Political Economy* **126**(5), 2072–2107.

Kirkeboen, L. J., Leuven, E. and Mogstad, M. [2016], 'Field of study, earnings, and self-selection', *The Quarterly Journal of Economics* **131**(3), 1057–1111.

Larroucau, T. and Rios, I. [2020], Dynamic college admissions and the determinants of students' college retention, Technical report, Technical Report 2020. and,"Do "Short-List" Students Report Truthfully.

Lucas, A. M. and Mbiti, I. M. [2014], 'Effects of school quality on student achievement: Discontinuity evidence from kenya', *American Economic Journal: Applied Economics* **6**(3), 234–263.

Neilson, C. [2019], 'The rise of centralized choice and assignment mechanisms in education markets around the world', *Unpublished manuscript* .

Niederle, M. and Vesterlund, L. [2010], 'Explaining the gender gap in math test scores: The role of competition', *Journal of economic perspectives* **24**(2), 129–44.

Pathak, P. A. [2011], 'The mechanism design approach to student assignment', *Annu. Rev. Econ.* **3**(1), 513–536.

Pop-Eleches, C. and Urquiola, M. [2013], 'Going to a better school: Effects and behavioral responses', *American Economic Review* **103**(4), 1289–1324.

Shi, P. [2022], 'Optimal priority-based allocation mechanisms', *Management Science* **68**(1), 171–188.

Stinebrickner, R. and Stinebrickner, T. R. [2006], 'What can be learned about peer effects using college roommates? evidence from new survey data and students from disadvantaged backgrounds', *Journal of public Economics* **90**(8-9), 1435–1454.

Svensson, L.-G. [1999], 'Strategy-proof allocation of indivisible goods', *Social Choice and Welfare* **16**(4), 557–567.

Appendices

A The admission exam

Table 5: Exam sections

	Questions
Math	12
Physics	12
Chemistry	12
Biology	12
Spanish	12
History	12
Geography	12
Civics and Ethics	12
Verbal ability	16
Math ability	16
Total	128

NOTE: This table shows the number of questions in different subjects that are part of the admission exam.

The admission exam is a multiple choice exam with 128 questions and five choices per question. Each correct answer is worth 1 point, and there are no negative points for wrong answers. Table 5 shows the different sections of the admission exam. The total score is calculated by adding up all the correct answers. Students must obtain a score no lower than 31 points in the admission exam to participate in the assignment process.

B Serial Dictatorship

All schools share a unique priority ordering, and each student defines her ROL. Then, the matching algorithm is as follows:

- Step 1: The first ranked student is assigned to the first school on her ROL.

- Step (k+1): For any $k \geq 1$, once the k^{th} student in the priority ranking has been assigned, the student ranked $(k+1)^{th}$ is assigned to the highest-ranked element of her ROL that still has a vacancy. If all of the schools in her ROL are full at that point, she is left unassigned, and the algorithm proceeds to the next student.
- Stop: The algorithm stops after all students have been processed.

Notice that this algorithm is a special case of the Student Proposing Deferred Acceptance algorithm in which all schools share the same ranking of students.

C Predetermined covariates

Table 6: Female

	female	female P2	female P3	female HB	female 2B
RD Estimate	0.011	0.004	0.001	0.012	0.014
	(0.012)	(0.015)	(0.017)	(0.022)	(0.010)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 7: Age

	age	age P2	age P3	age HB	age 2B
RD Estimate	0.022	0.044	0.014	0.002	0.022
	(0.027)	(0.036)	(0.051)	(0.052)	(0.024)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 8: GPA

	gpa	gpa P2	gpa P3	gpa HB	gpa 2B
RD Estimate	0.026	0.028	0.025	0.010	0.022
	(0.019)	(0.021)	(0.029)	(0.039)	(0.017)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 9: Income

	inc5k	inc5k P2	inc5k P3	inc5k HB	inc5k 2B
RD Estimate	-0.003	-0.004	-0.003	0.016	0.001
	(0.014)	(0.015)	(0.019)	(0.030)	(0.012)

NOTE: Standard errors in parenthesis. Income is a dummy variable indicating if the family monthly income is higher or lower that 5000 pesos.The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

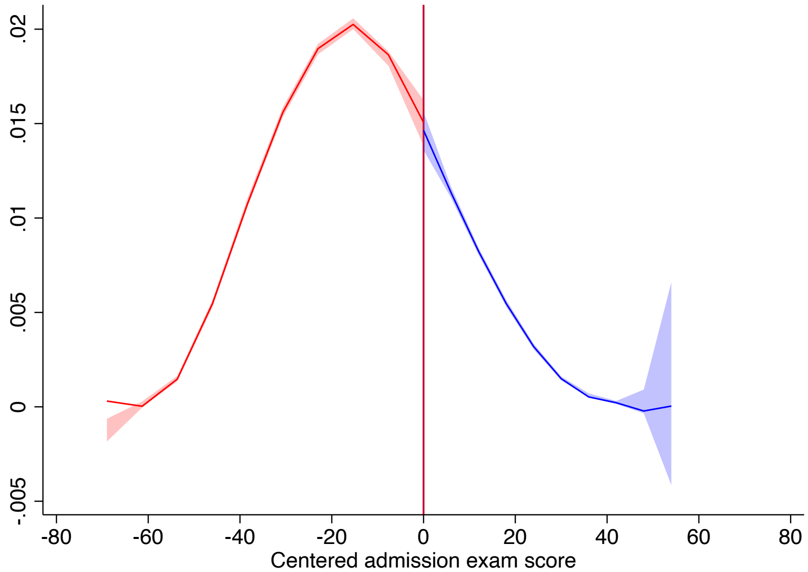
Table 10: Siblings

	siblings	siblings P2	siblings P3	siblings HB	siblings 2B
RD Estimate	0.013	0.019	0.025	0.084	0.009
	(0.037)	(0.043)	(0.050)	(0.077)	(0.032)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

D RDD validity: low GPA

Figure 13: Density of the running variable, low GPA



NOTE: This figure shows the density of the centered running variable for low GPA students. The shaded regions are 95% confidence intervals.

Table 11: Female

	female	female P2	female P3	female HB	female 2B
RD Estimate	0.002	-0.008	-0.008	0.016	0.008
	(0.016)	(0.021)	(0.023)	(0.030)	(0.014)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 12: Age

	age	age P2	age P3	age HB	age 2B
RD Estimate	0.060	0.096	0.086	0.026	0.045
	(0.050)	(0.068)	(0.080)	(0.099)	(0.044)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 13: GPA

	gpa	gpa P2	gpa P3	gpa HB	gpa 2B
RD Estimate	0.010	0.013	0.018	-0.005	0.007
	(0.014)	(0.016)	(0.020)	(0.030)	(0.012)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 14: Income

	inc5k	inc5k P2	inc5k P3	inc5k HB	inc5k 2B
RD Estimate	-0.001	0.001	0.006	0.026	0.006
	(0.021)	(0.027)	(0.030)	(0.046)	(0.018)

NOTE: Standard errors in parenthesis. Income is a dummy variable indicating if the family monthly income is higher or lower that 5000 pesos.The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

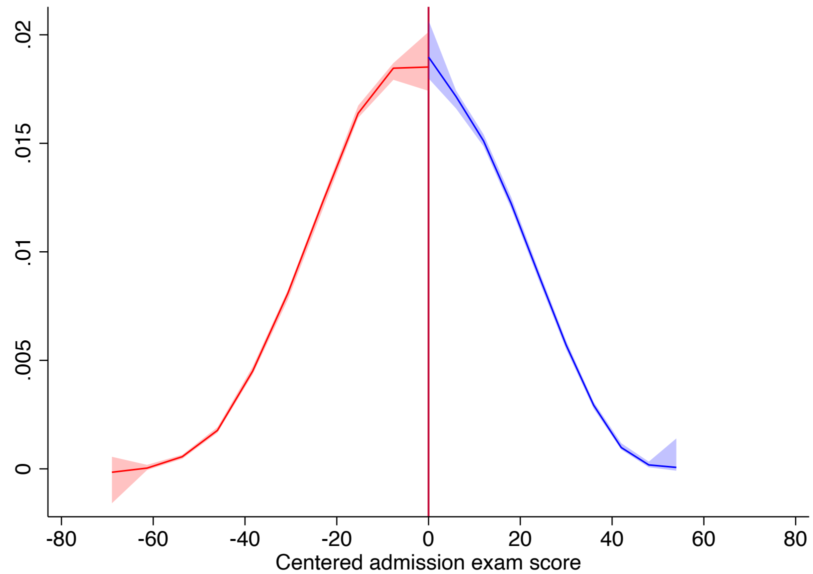
Table 15: Siblings

	siblings	siblings P2	siblings P3	siblings HB	siblings 2B
RD Estimate	0.032	0.056	0.126	0.213	0.025
	(0.056)	(0.069)	(0.085)	(0.122)	(0.048)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

E RDD validity: high GPA

Figure 14: Density of the running variable, high GPA



Note: This figure shows the density of the centered running variable for high GPA students. The shaded regions are 95% confidence intervals.

Table 16: Female

	female	female P2	female P3	female HB	female 2B
RD Estimate	0.014	0.008	0.004	0.019	0.017
	(0.016)	(0.021)	(0.025)	(0.032)	(0.014)

Note: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 17: Age

	age	age P2	age P3	age HB	age 2B
RD Estimate	0.010	0.017	-0.016	-0.027	0.002
	(0.031)	(0.042)	(0.058)	(0.057)	(0.028)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 18: GPA

	gpa	gpa P2	gpa P3	gpa HB	gpa 2B
RD Estimate	0.011	0.015	0.021	0.052	0.009
	(0.015)	(0.016)	(0.023)	(0.030)	(0.013)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 19: Income

	inc5k	inc5k P2	inc5k P3	inc5k HB	inc5k 2B
RD Estimate	-0.006	-0.005	-0.000	0.004	-0.007
	(0.018)	(0.022)	(0.027)	(0.036)	(0.016)

NOTE: Standard errors in parenthesis. Income is a dummy variable indicating if the family monthly income is higher or lower that 5000 pesos.The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 20: Siblings

	siblings	siblings P2	siblings P3	siblings HB	siblings 2B
RD Estimate	-0.008	-0.005	-0.024	-0.032	-0.014
	(0.041)	(0.060)	(0.074)	(0.078)	(0.037)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

F Main Estimates

Table 21: On-time graduation

	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
RD Estimate	-0.064	-0.061	-0.057	-0.050	-0.064
	(0.012)	(0.015)	(0.018)	(0.026)	(0.011)

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Table 22: On-time graduation by GPA

	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
High GPA	0.015	0.017	0.018	0.025	0.006
	(0.017)	(0.023)	(0.025)	(0.035)	(0.015)
Low GPA	-0.149	-0.148	-0.152	-0.127	-0.143
	(0.018)	(0.022)	(0.023)	(0.035)	(0.014)
Diff	0.164	0.165	0.170	0.153	0.150
Diff SE	0.025	0.032	0.034	0.050	0.021

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

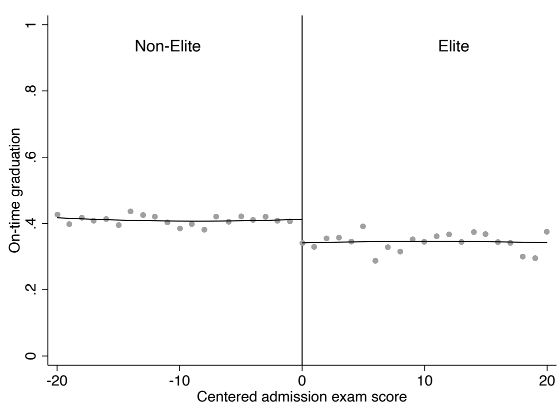
Table 23: On-time graduation by gender

	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
Girls	0.011	0.018	0.022	0.018	-0.013
	(0.020)	(0.023)	(0.027)	(0.036)	(0.015)
Boys	-0.130	-0.134	-0.136	-0.121	-0.121
	(0.019)	(0.019)	(0.025)	(0.036)	(0.015)
Diff	0.141	0.151	0.158	0.139	0.107
Diff SE	0.028	0.030	0.036	0.051	0.022

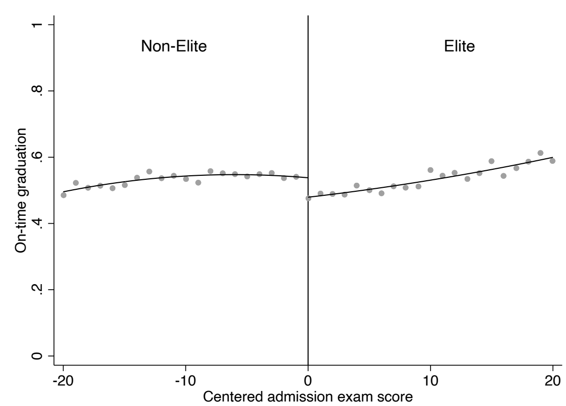
NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

G RDD by low-stakes

Figure 15: Elite school admission and on-time graduation by low-stakes exam



(a) On-time graduation: low low-stakes exam score



(b) On-time graduation: high low-stakes exam score

NOTE: This figure shows binned means of on-time graduation around the elite admission thresholds for students with high and low scores in the low-stakes standardized exam.

Table 24: On-time graduation by low-stakes exam

	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
High LS	-0.058	-0.057	-0.057	-0.055	-0.060
	(0.017)	(0.022)	(0.026)	(0.034)	(0.015)
Low LS	-0.073	-0.076	-0.064	-0.061	-0.068
	(0.018)	(0.023)	(0.029)	(0.038)	(0.016)
Diff	0.015	0.019	0.007	0.006	0.008
Diff SE	0.025	0.032	0.039	0.051	0.022

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

H RDD by residuals

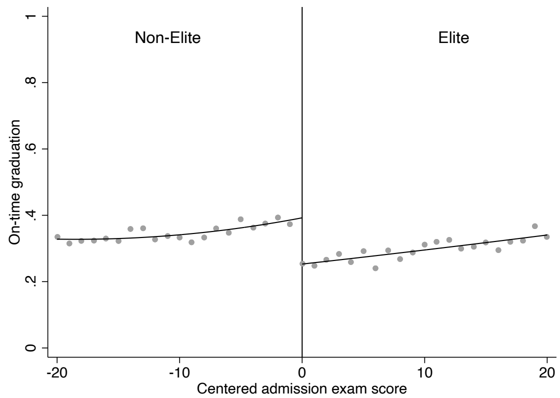
Define:

$$GPA_i = \alpha_0 + \alpha_1 s_i + \alpha_2 ls_i + \epsilon_i, \tag{7}$$

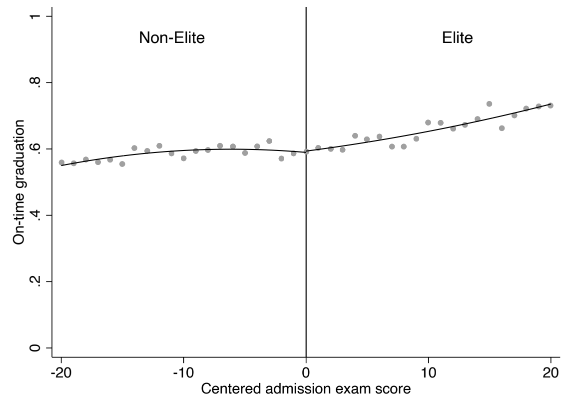
where s_i is the score in the admission exam score, ls_i is the score in the low-stakes exam, and GPA_i is middle school GPA.

We estimate equation 7 and use $\hat{\epsilon}_i$ to define high and low residuals (above and below median).

Figure 16: Elite school admission and on-time graduation by GPA residuals



(a) Graduation: low $\hat{\epsilon}_i$



(b) Graduation: high $\hat{\epsilon}_i$

NOTE: This figure shows binned means of on-time graduation around the elite admission thresholds for students with high and low GPA residuals.

Table 25: On-time graduation by GPA residuals

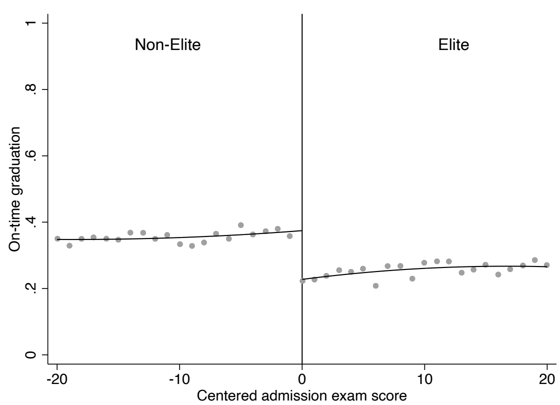
	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
High Resid	0.006	0.017	0.019	0.033	0.005
	(0.016)	(0.022)	(0.025)	(0.036)	(0.015)
Low Resid	-0.144	-0.146	-0.133	-0.121	-0.139
	(0.017)	(0.020)	(0.025)	(0.034)	(0.014)
Diff	0.151	0.162	0.151	0.154	0.144
Diff SE	0.023	0.030	0.035	0.050	0.021

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

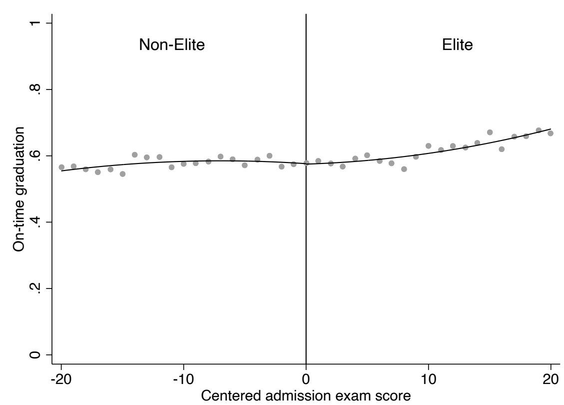
I Above and below-median within middle school GPA distribution

Instead of separating students as having above or below median GPAs in the entire distribution of GPAs, we define above and below median GPA students relative to the distribution of GPAs within their middle schools. We do this to control for middle school fixed-effects and ensure that our results are not driven by attending particular subgroups of middle schools. In Figure 17, we show that our previous results are unchanged by this alternative definition of high and low GPA students.

Figure 17: Elite school admission and on-time graduation by GPA ranking



(a) Graduation: low GPA ranking



(b) Graduation: high GPA ranking

NOTE: This figure shows binned means of on-time graduation around the elite admission thresholds for students above and below median within middle school percentile ranking by GPA.

Table 26: On-time graduation by GPA ranking

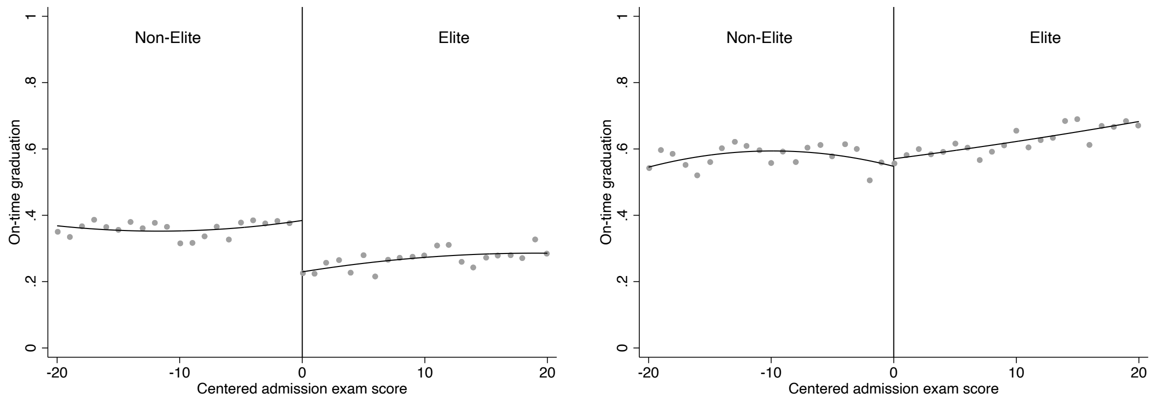
	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
High Rank	0.010	0.010	0.013	0.025	0.001
	(0.018)	(0.022)	(0.023)	(0.034)	(0.015)
Low Rank	-0.155	-0.150	-0.149	-0.128	-0.148
	(0.018)	(0.023)	(0.025)	(0.036)	(0.015)
Diff	0.165	0.160	0.162	0.153	0.149
Diff SE	0.025	0.032	0.034	0.050	0.021

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

J Elite schools with high and low cut-offs

For the RDD analysis we pool k groups of students that share a common elite school cut-off c_k. In this appendix we show that the effects on on-time graduation do not depend on elite schools having high or low cut-offs. Instead of pooling together our k groups, we separate these groups into low and high elite school cut-offs and repeat the analysis for each sub-sample.

Figure 18: Elite school admission and on-time graduation: low elite cut-offs



(a) Graduation: low GPA

(b) Graduation: high GPA

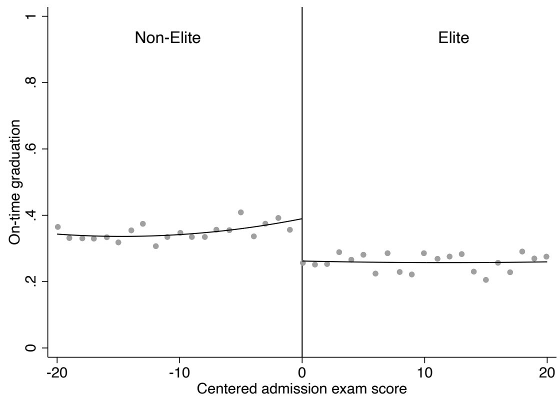
NOTE: This figure shows binned means of on-time graduation around low elite school admission thresholds.

Table 27: On-time graduation, low elite cut-offs

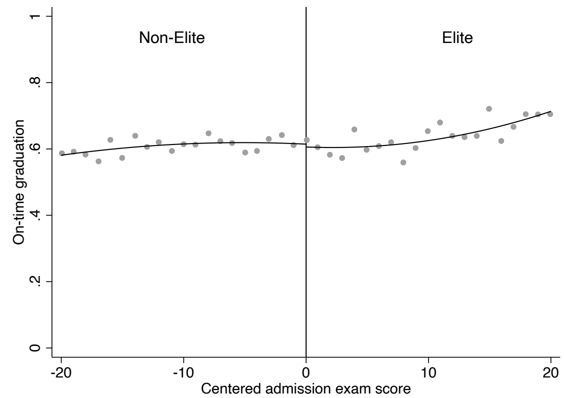
	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
High GPA	0.044	0.048	0.051	0.018	0.025
	(0.028)	(0.035)	(0.041)	(0.052)	(0.022)
Low GPA	-0.166	-0.181	-0.135	-0.147	-0.159
	(0.026)	(0.027)	(0.038)	(0.048)	(0.019)
Diff	0.210	0.230	0.186	0.165	0.183
Diff SE	0.038	0.044	0.056	0.071	0.029

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

Figure 19: Elite school admission and on-time graduation on time: high elite cut-offs



(a) Graduation: low GPA



(b) Graduation: high GPA

NOTE: This figure shows binned means of on-time graduation around high elite school admission thresholds.

Table 28: On-time graduation, high elite cut-offs

	Grad	Grad P2	Grad P3	Grad HB	Grad 2B
High GPA	-0.005	-0.007	-0.014	0.052	-0.007
	(0.026)	(0.030)	(0.037)	(0.054)	(0.022)
Low GPA	-0.121	-0.113	-0.107	-0.094	-0.125
	(0.028)	(0.034)	(0.038)	(0.059)	(0.023)
Diff	0.116	0.106	0.094	0.146	0.118
Diff SE	0.038	0.046	0.053	0.080	0.032

NOTE: Standard errors in parenthesis. The first column show the estimates of a local linear regression using the optimal bandwidth. The second column uses a polynomial of degree two for the running variable. The third column uses a polynomial of degree three for the running variable. The fourth column uses a local linear regression within half the optimal bandwidth. The fifth column uses a local linear regression within twice the optimal bandwidth.

K GPA and gender

To compare two subgroups while holding another observable characteristic constant, we follow the approach proposed by Gerardino et al. [2017]. For example, in our case, the subgroup of students with high GPAs has a higher share of girls than those with low GPAs. Thus, the method allows us to reweight the observations to keep gender balanced across subgroups while studying heterogeneous effects between high- and low-GPA students.

Table 29: RDD estimates using propensity score weighting

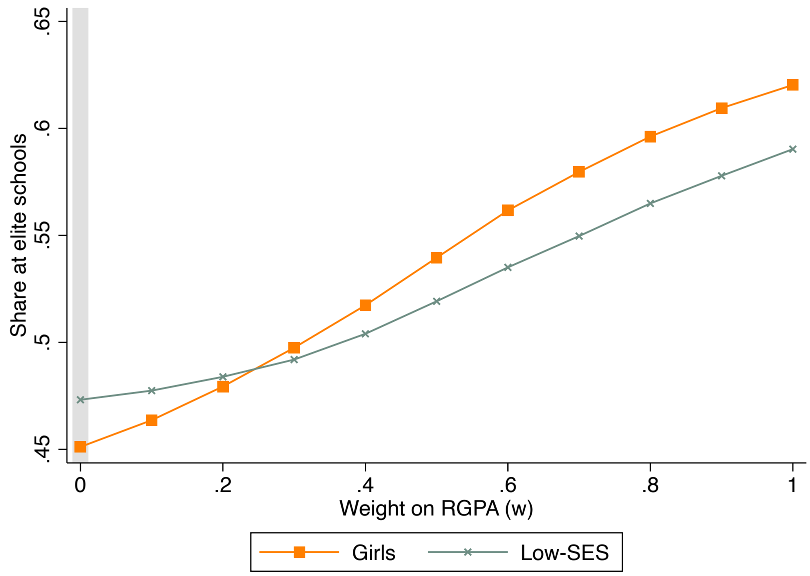
	(1) Gender balanced	(2) GPA balanced
Low GPA	-0.110	
	(0.017)	
High GPA	-0.017	
	(0.012)	
Boys		-0.077
		(0.015)
Girls		-0.047
		(0.016)
Diff	.093	.029
	(.023)	(.023)

NOTE: The outcome for all columns is on-time graduation. The first column shows RDD estimates for low and high GPA students while holding gender balanced across subgroups. The second column shows RDD estimates for boys and girls while holding GPA balanced across subgroups. Diff indicates the difference in treatment effects across subgroups. Standard errors in parenthesis.

L RGPA

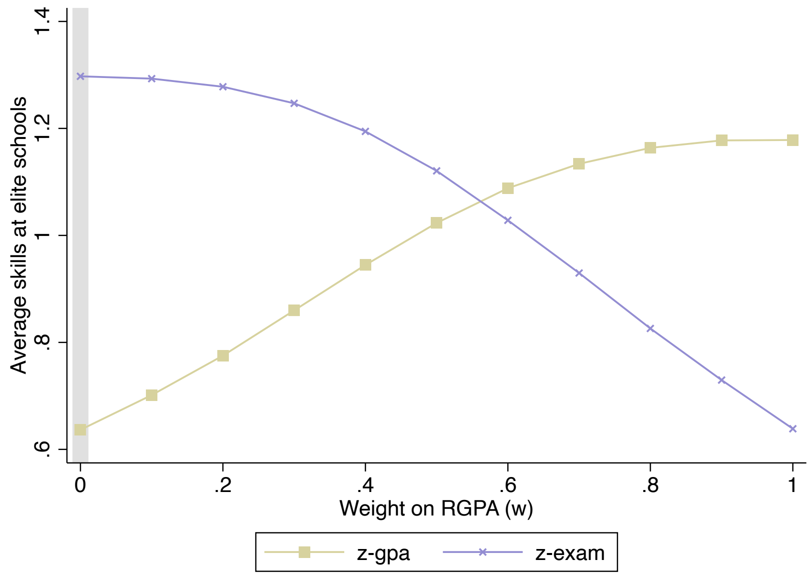
In this section, we include the results of a counterfactual analysis that increasingly adds weight to applicants' within-middle school percentile ranking.

Figure 20: Composition of students at elite schools



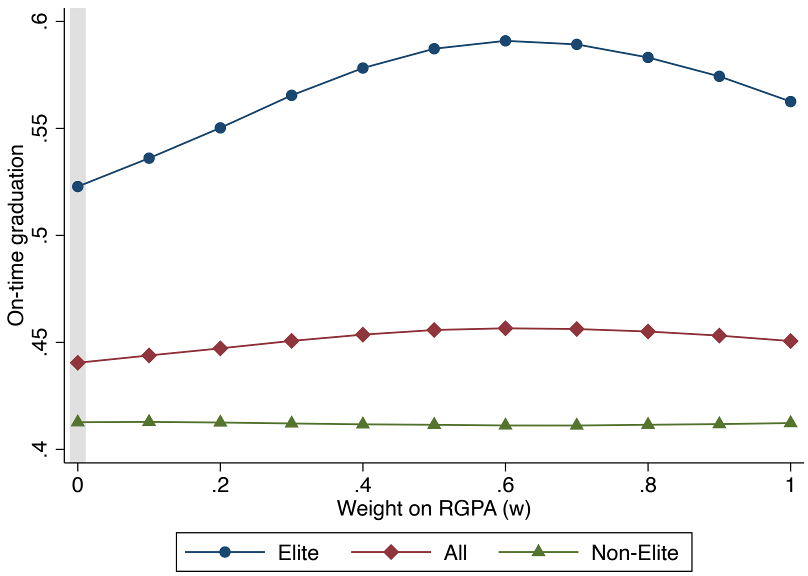
Note: This figure shows the share of girls and low-SES students admitted to elite schools in each counterfactual equilibrium associated with a combination of weights on RGPA and the admission exam score. The x-axis indicates the weight on RGPA (w). The weight on the admission exam score is $(1-w)$. We define a low-SES student as one whose family income is lower than 5000 Mexican pesos per month (458 USD).

Figure 21: Skills of students at elite schools



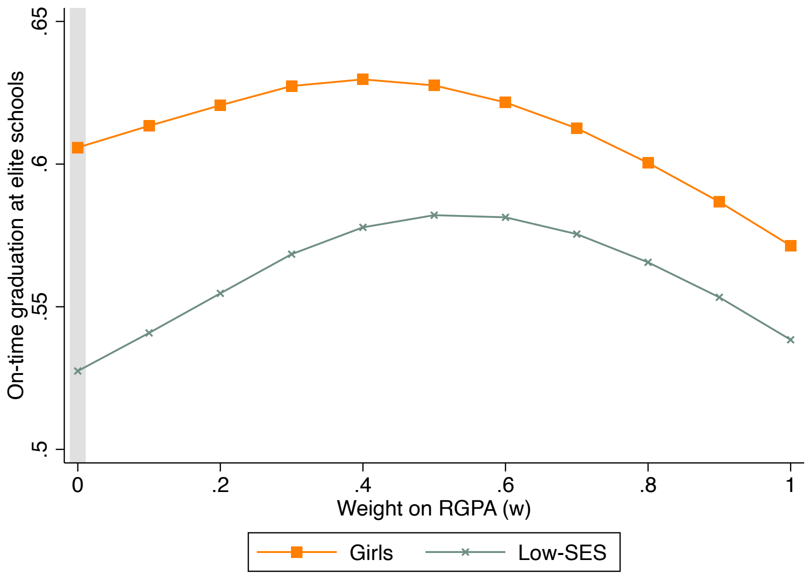
NOTE: This figure shows the average standardized admission exam score and RGPA of students admitted to elite schools in each counterfactual equilibrium associated with a combination of weights on RGPA and the admission exam score. The x-axis indicates the weight on RGPA (w). The weight on the admission exam score is $(1 - w)$.

Figure 22: On-time graduation



NOTE: This figure shows the average on-time graduation rate for each counterfactual equilibrium associated with a combination of weights on RGPA and the admission exam score. We include this average for three groups of schools: elite, non-elite, and all. We define on-time graduation as graduating three years after admission, which reflects normal grade progression during high school. The x-axis indicates the weight on RGPA (w). The weight on the admission exam score is $(1 - w)$.

Figure 23: On-time graduation at elite schools



NOTE: This figure shows the average on-time graduation rate at elite schools for each counterfactual equilibrium associated with a combination of weights on RGPA and the admission exam score. We include this average for two groups of students: girls and low-SES. We define on-time graduation as graduating three years after admission, which reflects normal grade progression during high school. The x-axis indicates the weight on RGPA (w). The weight on the admission exam score is $(1 - w)$. We define a low-SES student as one whose monthly family income is lower than 5000 Mexican pesos (458 USD).

M CGPA

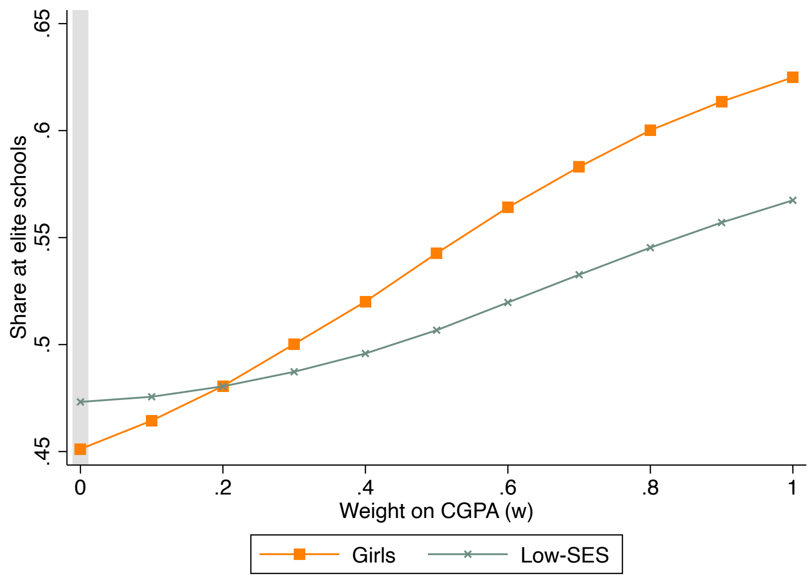
In this section, we include the results of a counterfactual analysis that increasingly adds weight to applicants' GPAs clean of middle school fixed effects. To implement this alternative, we regress GPA on the low-stakes exam and middle school fixed-effects as in Equation 8. We then subtract the middle school effects from GPA to obtain a measure we call $CGPA$.

$$GPA_{im} = \alpha_m + \beta ls_i + \nu_{im} \tag{8}$$

$$CGPA_{im} = GPA_{im} - \hat{\alpha}_m, \tag{9}$$

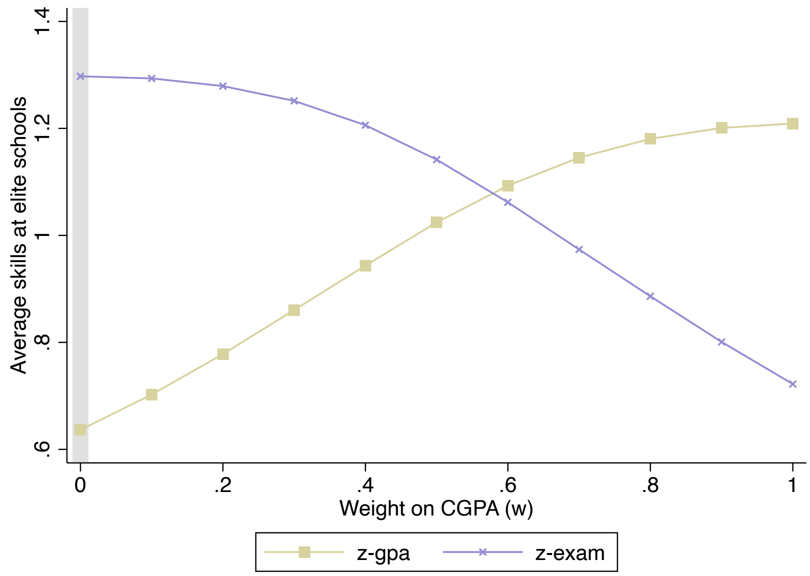
where i indicates student and m indicates middle school.

Figure 24: Composition of students at elite schools



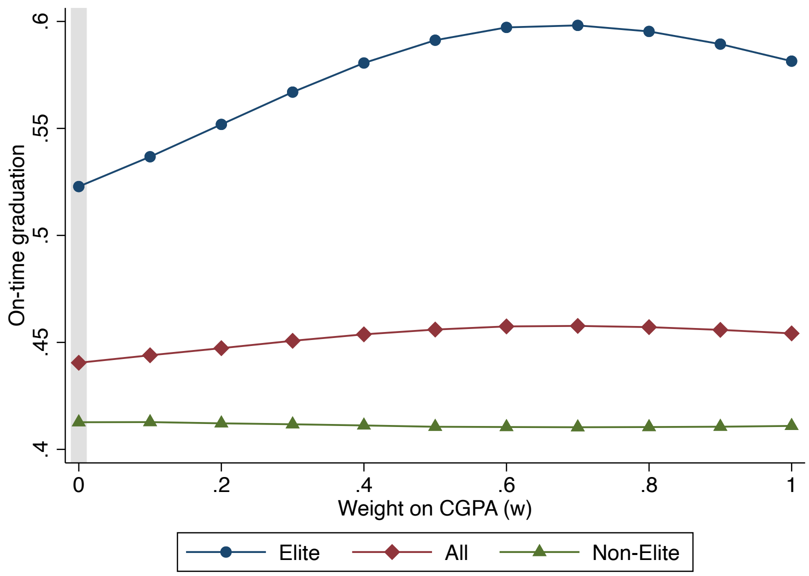
NOTE: This figure shows the share of girls and low-SES students admitted to elite schools in each counterfactual equilibrium associated with a combination of weights on CGPA and the admission exam score. The x-axis indicates the weight on CGPA (w). The weight on the admission exam score is $(1-w)$. We define a low-SES student as one whose family income is lower than 5000 Mexican pesos per month (458 USD).

Figure 25: Skills of students at elite schools



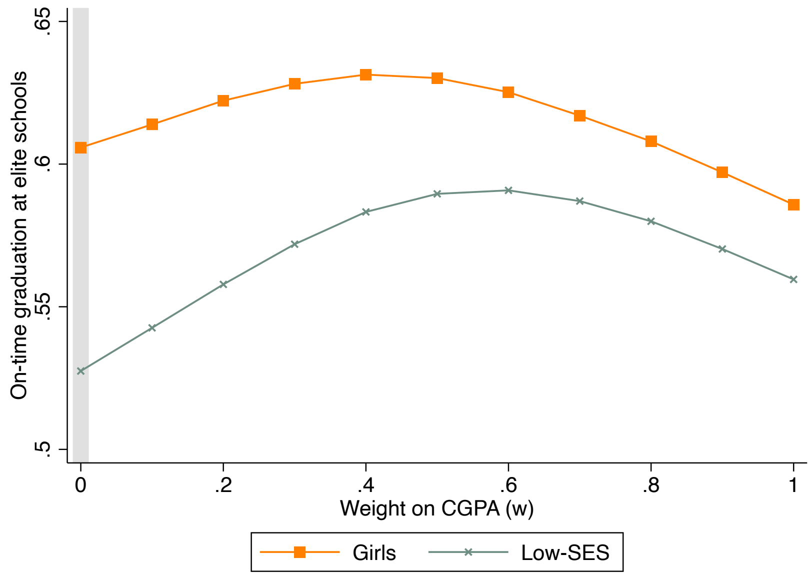
Note: This figure shows the average standardized admission exam score and GPA of students admitted to elite schools in each counterfactual equilibrium associated with a combination of weights on CGPA and the admission exam score. The x-axis indicates the weight on CGPA (w). The weight on the admission exam score is $(1 - w)$.

Figure 26: On-time graduation



NOTE: This figure shows the average on-time graduation rate for each counterfactual equilibrium associated with a combination of weights on CGPA and the admission exam score. We include this average for three groups of schools: elite, non-elite, and all. We define on-time graduation as graduating three years after admission, which reflects normal grade progression during high school. The x-axis indicates the weight on CGPA (w). The weight on the admission exam score is $(1 - w)$.

Figure 27: On-time graduation at elite schools



Note: This figure shows the average on-time graduation rate at elite schools for each counterfactual equilibrium associated with a combination of weights on CGPA and the admission exam score. We include this average for two groups of students: girls and low-SES. We define on-time graduation as graduating three years after admission, which reflects normal grade progression during high school. The x-axis indicates the weight on CGPA (w). The weight on the admission exam score is $(1 - w)$. We define a low-SES student as one whose monthly family income is lower than 5000 Mexican pesos (458 USD).