School Choice, Mismatch, and Graduation

Marco Pariguana* — Tulane University

Maria Elena Ortega-Hesles — VIA Educacion

Abstract

This paper studies the effects of changing the priority ordering in the centralized high school admission system in Mexico City. Academically elite schools experience excess demand, while admission priorities are based solely on a standardized admission exam. The system ignores other skill measures such as middle school grade point average (GPA), which may better capture non-cognitive skills that are important for later education and life-cycle outcomes. Using a Regression Discontinuity Design (RDD), we first show that marginal admission to an elite high school decreases the graduation probability for students with low middle school GPA and increases it for students with high middle school GPA. Guided by this evidence, we then study the effects of a counterfactual admission policy wherein the priority index flexibly combines information on both the admission exam score and the middle school overall GPA. Our counterfactual results show that more females and low-income students would be admitted to elite schools, and the graduation rate at elite schools would increase by six percentage points. Overall, our findings show that including the information contained in GPA in the priority ordering improves equity of access, decreases mismatch, and increases graduation.

*I would like to thank Salvador Navarro, Matteo Bobba, and Todd Stinebrickner for their guidance and support. I would also like to thank Lance Lochner, Audra Bowlus, Rory McGee, Roy Allen, and Sylvia Blom for their helpful feedback.

1 Introduction

> The predictive power of grades shows the folly of throwing away the information contained in individual teacher assessments when predicting success in life.
>
> *Borghans, Golsteyn, Heckman, and Humphries (2016)*

The use of centralized education systems that assign students to public schools is expanding worldwide [Neilson, 2019].[1] Because schools have limited seats and some schools experience higher demand than offered seats, system designers need a way to ration the available seats [Shi, 2022]. Since using prices as a rationing mechanism is not feasible in public education, and schools are not allowed to have preferences over students, policymakers define priority orderings that assign a priority index to each student. Priority orderings solve the excess demand problem by determining which students gain admission to over-subscribed schools. Typical components of priority orderings are siblings, residential zones, lotteries, a standardized exam, and GPA.

In practice, there is substantial heterogeneity in how current systems define their priority orderings. Understanding the consequences of implementing a given priority ordering is essential for several reasons. First, the inputs used to create a priority ordering within a system could affect the equity of access. For example, consider a case where males score higher on standardized exams while females have higher GPAs. If the system only uses a standardized exam to prioritize students, males will have more access than females to highly demanded schools. Second, a particular priority ordering could affect the graduation rate if it creates a mismatch between students' skills and schools' academic requirements. For example, giving higher admission priorities for the most academically demanding schools to students without the skills needed to graduate from them may potentially result in low graduation rates.

In this paper, we explore the issues mentioned above by studying the case of the centralized high school admission system in Mexico City. In this system, students' priority index is solely based on their scores in a system-wide admission exam. The system has different types of high schools. Elite high schools are more academically

[1] See Appendix A for examples of centralized education markets and their common structure.

demanding and experience much higher demand than available seats. Both elite and non-elite schools use the same priority index.[2] We focus on the following question: Is the system ignoring valuable information that could be used to create better matches? Specifically, the system could benefit from broadening the priority index by also considering the information contained in GPA. We focus on GPA as a potential channel to improve student-school matches to the extent that previous literature shows that grades measure non-cognitive skills (e.g., effort and self-control) to a higher degree than achievement tests and that non-cognitive skills are important determinants of desirable educational outcomes such as graduation [Stinebrickner and Stinebrickner, 2006; Duckworth et al., 2012; Borghans et al., 2016; Jackson, 2018].

We use the administrative records of all the participants in the centralized high school admission process in Mexico City. We complement the admission data by collecting official high school graduation records 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 high-school 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 all the information necessary to exactly replicate the observed student-school matches plus additional student characteristics (such as the middle school GPA) that were not used to define priorities in the system. We use this additional information to simulate alternative allocations of students.

We first shed light on the importance of the skills captured by GPA and their influence on students' probability of graduation from the most over-subscribed schools in the system (i.e., elite schools). We do so by estimating the effect of being marginally admitted to an elite school on the probability of graduation. The assignment mechanism creates exogenously determined admission cut-offs for elite school admission.

[2]Elite schools also have a minimum GPA requirement of 7/10, but most of the students meet this requirement (more than 90%). The minimum GPA to graduate from middle school is 6/10.

[3]The matching algorithm is the Serial Dictatorship which is strategy-proof [Svensson, 1999]. In addition, in Mexico City, students submit their ranking of schools before they know their priority index. Uncertainty in the priority index incentivizes truthful revelation of preferences.

Using a Regression Discontinuity Design (RDD), we find that the effect of marginal admission to an elite school on the probability of graduation is close to zero and not statistically significant. However, students at the margin of admission to an elite school are very heterogeneous in terms of their middle-school GPAs. To study heterogeneity in the effect of interest, we estimate an RDD separately for students with above and below-median GPAs. We find that admission to an elite school *decreases* the probability of graduation by eight percentage points for students with below-median GPA. For students with above-median GPA, elite-school admission is associated with an *increase* in their probability of graduation of seven percentage points. The lack of an overall effect is explained by these two effects canceling each other out. Our results indicate that to benefit from a higher graduation probability when gaining marginal admission to an elite school, a student requires enough of the skills that GPA better captures.

We also implement RDDs separately for males and females and find heterogeneous effects by gender. We find that the effect for males is similar to the one for students with low GPAs, and the effect for females is similar to that for students with high GPAs. Males experience a decrease in their graduation probability, while females experience an increase in their graduation probability. A potential explanation behind these results is that in our data, at every percentile of the admission exam score distribution, females have higher GPAs than males.

In terms of our research question, our first set of results imply that, even for students at the margin of admission to an elite school, an assignment mechanism that relies on a scalar measure of skills may create mismatch by missing out on important information about students' academic potential.

We then study the effects of a counterfactual admission policy that could better match students to schools. Our approach combines the reassignment of students to schools prompted by a change in the priority structure with a flexible discrete choice graduation model. We model the youth's decision to complete high school because our counterfactual admission policy affects students beyond the margin of admission to elite schools for whom our RDD estimates may not be informative.[4] We follow Dale and Krueger [2014] in that our graduation model includes controls for the characteristics

[4]For instance, under treatment effect heterogeneity by the running variable, RDD estimates are only informative for students at the margin [Rokkanen, 2015].

of students' application lists to deal with commonly unobserved students' preferences that could affect graduation. We validate our model predictions by showing that they reproduce the main patterns we previously obtained in our RDD analysis even though we did not target them when estimating the model.

Our counterfactual admission policy changes elite schools' priority index to equally weight GPA and the admission exam score, while non-elite schools still follow the status-quo priority rule.[5] Because of potential concerns regarding differential grading standards between middle schools, we also consider a case where instead of GPA, elite schools' priority index includes within middle school percentile ranking by GPA. Our results are not sensitive to this change. We only change the priorities of elite schools because those are the schools for which we showed heterogeneous results in the RDD analysis. In addition, we show that GPA influences elite school graduation more than it does non-elite school graduation.

Under the new priority structure, we run a more general version of the same assignment algorithm that allows schools to have differentiated priorities. The new algorithm preserves the theoretical properties of the one that is currently in place (e.g., strategy-proof).[6] We assume that students' ranking of schools does not change in the counterfactual because students' preferences do not depend on the system priority structure under a strategy-proof assignment algorithm. However, the change in priorities does affect the assignment of students to elite and non-elite schools.

Our counterfactual generates important changes in the composition of students assigned to elite schools. First, it increases the share of females assigned to them by nine percentage points. Females gain more access to elite schools thanks to receiving a higher priority index for their relatively high GPAs. Second, the share of low-income students at elite schools increases. Low-income students gain more access to elite schools because GPA is less stratified by income than the admission exam score.

Our graduation model gives us a mapping from students' characteristics to their probability of graduation from each school. We combine the estimated parameters from

[5]As a robustness check, we do a counterfactual where all schools in the system use the information contained in GPA. Our results are not affected by this change.

[6]We also maintain the timing of the process. Students do not know their priority index before they submit their ranking of schools which incentivizes truthful revelation of preferences.

our model and the new students' characteristics allocated to each school to predict graduation rates in the counterfactual. We find that the graduation rate from elite schools increases six percentage points. The graduation rate increases because the counterfactual matches elite schools with higher GPA students who have more of the skills necessary to graduate from them. We then focus on two subgroups of students, the placed and displaced students. A placed student changes her assignment from a non-elite school in the baseline to an elite school in the counterfactual. A displaced student goes from being assigned to an elite school in the baseline to a non-elite school in the counterfactual. The graduation rate of both the placed and displaced students is higher in the counterfactual than their own baseline graduation rate. We take this as evidence of mismatch in the baseline.

Lastly, since our counterfactual assigns students to schools they prefer more or less, we quantify its effects on students' ex-ante welfare. For example, a student could prefer less a school where she is more likely to graduate if she values more other school characteristic such as distance. Students' rankings of schools give us ordinal information about their preferences. However, students could have different cardinal valuations for schools and, depending on the intensity of their preferences, be affected differently by the change in admission policy. To facilitate comparisons of gains and losses on the same scale, we use students' ranking of schools and estimate students' indirect utilities in willingness-to-travel space to measure utility in miles. We find that in our counterfactual, females' welfare increases, and males' welfare decreases by approximately the same amount. In addition, low-income students' welfare increases while high-income students' welfare decreases also by the same amount. Behind our effects on students' welfare is that females and low-income students gain access to their top choices, while males and high-income students see less access to their top choices. At the same time, the overall efficiency of the system remains unchanged.

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 in a centralized system. Neilson [2019] reviews centralized education systems worldwide and highlights that the consequences of implementing different priority structures are currently understudied. Shi [2022] and Abdulkadiroğlu et al. [2021] are the more related papers to ours. Their focus is on finding optimal priority structures in centralized education systems. We complement their work by looking at students' downstream outcomes, such as graduation rates, that are crucial to assess mismatch within an assignment system.[7]

Second, we also contribute to the literature on using achievement tests and grades in education policy. The informational content of grades grows in importance when considering non-cognitive skills. Stinebrickner and Stinebrickner [2006] find that high school GPA is a strong predictor of study effort during college, while the ACT score is not. Duckworth et al. [2012] show that grades measure students' self-control more than achievement tests. Borghans et al. [2016] show that grades measure personality more than achievement tests and that personality is an important determinant of many relevant life outcomes. The informational content of grades calls into question the prominent role of achievement tests in educational policy. For example, Heckman et al. [2014] study a policy that treats the GED as equivalent to a high school diploma, while Duckworth et al. [2012] consider a policy that conditions school funding on the use of standardized tests. Our paper complements this previous literature by focusing on the consequences of a policy that ignores the informational content of grades when prioritizing students in a centralized education market.

Third, we contribute to the literature on heterogeneous treatment effects in an RDD by focusing on a case where a null average treatment effect occurs because positive and negative effects cancel each other out. Hsu and Shen [2019] design a test for heterogeneous treatment effects in RDDs and find that the effect of attending a better high school on the take-up rate of an exit exam is heterogeneous. They argue that heterogeneous treatment effects could explain previous findings showing a null average effect. Becker et al. [2013] implement an RDD and find that the effect of regional transfers in the European Union depends on regions having enough absorptive capacity

[7] 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. Our focus on graduation rates gains relevance because students do not necessarily choose schools based on their match quality [Abdulkadiroğlu et al., 2020], yet policymakers care about graduation rates.

to take advantage of them. Our results parallel theirs in that the effect of marginal admission to an elite school depends on a student having enough of the skills required to take advantage of what elite schools offer.

The remainder of the paper proceeds as follows. Section 2 describes the education system in Mexico City. Section 3 provides details about the 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 counterfactual admission policy and its effects on assignment, graduation, and students' ex-ante welfare. Section 6 contains our conclusions.

2 Education in Mexico City

The schooling system in Mexico has three levels: elementary school, middle school, and high school. Elementary school is six years in length, middle school and high school are both three years. The centralized high school education system in Mexico City encompasses all 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 schools outside Mexico City, already have a middle school certificate, or are enrolled in adult education.

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.

Table 1: Sub-systems in 2007

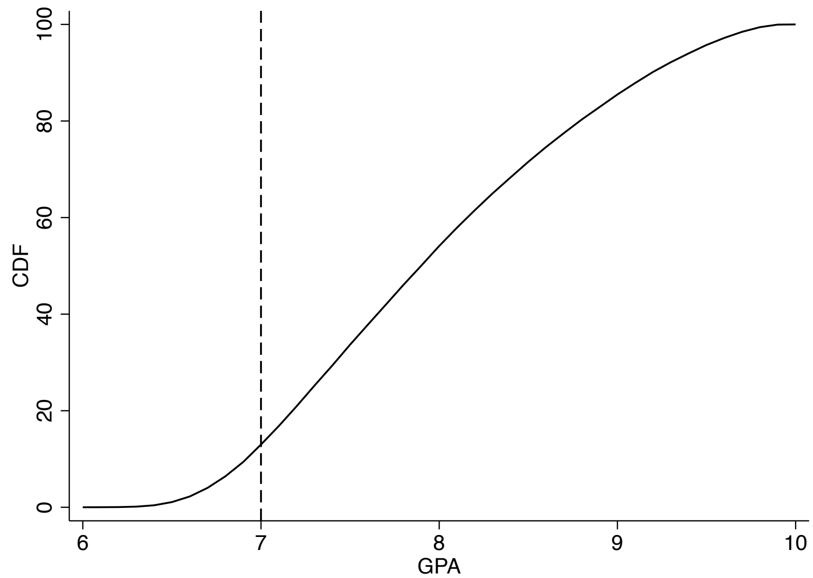
	Number of Schools	Seats	First in ROL	Admission Cut-Off
SUB 1	14	14.1%	48.5%	86.3
SUB 2	16	8.7%	14.5%	79.6
SUB 3	1	0.4%	0.7%	74.0
SUB 4	2	0.9%	0.5%	60.5
SUB 5	40	16.9%	6.1%	49.2
SUB 6	215	22.8%	16.1%	47.0
SUB 7	186	17.6%	7.7%	44.5
SUB 8	179	18.4%	5.8%	35.8
SUB 9	5	0.3%	0.2%	32.4
Total	658	100.0%	100.0%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

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 include 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-offs. We define an admission cut-off as the minimum score obtained by a student assigned to a given school in the previous admission cycle. The scores in the admission exam are between 31 and 128 points. The fourth column of Table 1 shows that elite schools' average admission cut-offs are the highest in the system.

Every year around 300,000 students participate in the centralized high school admission process. In February, students receive an information booklet describing the steps they need to follow. The information booklet also lists all the 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 exact 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 B.

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 requirement (Figure 1).

Figure 1: Elite schools minimum GPA requirement



Before implementing the matching algorithm, the 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 decide to admit or reject all tied students. For example, if a school has ten remaining seats 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 Student Proposing Deferred Acceptance (SPDA).[8] Since all schools use the same priority ordering, the algorithm is equivalent to 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 the Serial Dictatorship algorithm in Appendix D.

After implementing the matching algorithm, a student can be matched or un-

[8]We include a description of this algorithm in Appendix C.

matched. There are two reasons why some students are unmatched. First, some students do not clear the cut-off for any of the schools they list in their ROLs. Second, some students only apply to elite schools and do not meet the minimum GPA requirement. Unmatched students get the chance to register into schools that still have 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 for the analysis. In that year, there were a total of 256,335 students applying to 658 high schools. We observe students' admission exam score, ROL, GPA, assigned school, and socio-demographic characteristics such as gender and parental income. In Table 3 we include descriptive statistics of the population of applicants. Students assigned to elite schools have higher admission exam scores, higher GPAs, and a larger share of them are male.

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)	-
	256,335	54,654	162,063	39,618

On the high school side, we have information on the number of seats offered by each school, 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 replicate the student-school matches observed in the data gives us confidence in the transparency of the admission system.

Table 3: Matching outcome 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

We collect administrative graduation records from 2010-2012 (3-5 years after admission) to measure graduation. Because high school duration is three years, not graduating by 2012 is likely to measure drop-out. We obtained graduation records for all the students assigned to eight out 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 graduation using students' participation in a standardized exam they take during the last semester of high school Dustan et al. [2017]. Not all the schools participate in this exam, but all the schools in our missing sub-system do so. To be consistent in our definition of graduation, we use exam participation in any year between 2010-2012. We employ students' national identification numbers to merge the admissions data with the graduation or exam records.

Our data collection efforts provide us with three major advantages. First, we observe application and graduation records for a large number of students, which allows us to study heterogeneity in an RDD (Section 4). Second, thanks to the properties of the matching algorithm in place and the timing of the admission process, we observe strategy-proof measures of students' ranking of schools (i.e., their preferences). Third, having information on GPA allows us to explore a counterfactual admission policy that uses the information contained in this measurement to define alternative priority structures (Section 5).

Before proceeding with the analysis, we highlight two pieces of descriptive evidence. First, the graduation rate from elite schools in Mexico City is low (65%). Second, previous GPA matters for elite school graduation more than it does for non-elite school graduation. We show evidence on this second point in Appendix E where include the results of estimating simple linear probability models of high school graduation for elite and non-elite schools.

4 Regression Discontinuity Evidence

4.1 Setup

All elite schools are over-subscribed, 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 graduation. We treat admission as equal to enrollment because enrollment at elite schools is almost universal. In our data, the enrollment rate for students admitted to an elite school is 97.42%.

We follow Dustan et al. [2017] and construct a sample of students assigned to an elite school with a score above or equal to a cut-off and assigned to a non-elite school otherwise. We impose three sample restrictions. First, we exclude all students that are ineligible 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 that have applied to at least one elite school and one non-elite school. Third, we only include students that rank elite schools higher than non-elite schools. The purpose of the last restriction is to select students with similar preferences in that they prefer elite schools to non-elite schools.

The design follows the same intuition of Kirkeboen et al. [2016] strategy to estimate the effect of admission to a particular institution. 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 their second-best a non-elite school in the local institution ranking (i.e., same preferences around their admission score). However, in addition to students having the same preferences in the local institution ranking, we are only considering students that prefer elite to non-elite schools in the full ranking. We can impose this last restriction because most of the students who apply to both types of schools rank elite schools higher than non-elite schools. The previous restriction excludes 815 (0.76%) students, and our results are not sensitive to including or excluding these 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 minimum cut-off among the elite schools she included in her application. Specifically, we define $k = 30$ groups of students that share a c_k. Within each group k, the following condition is satisfied:

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

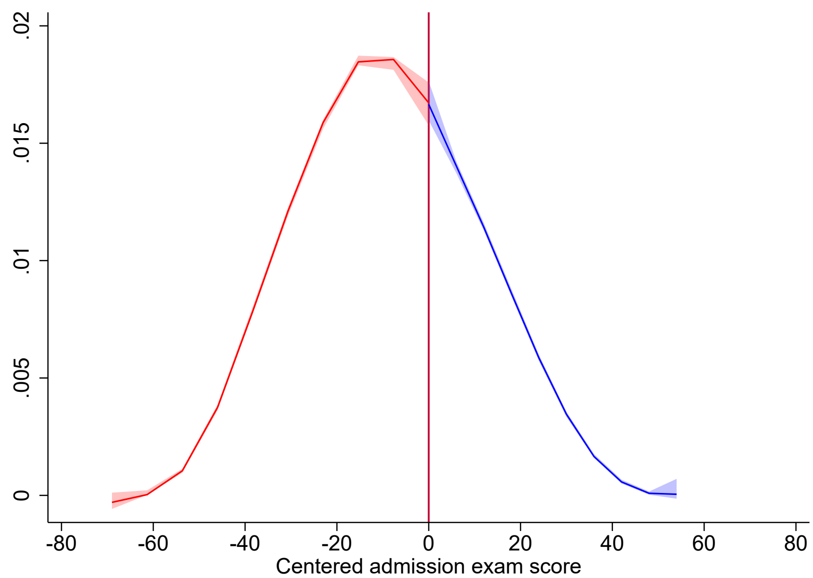
To estimate our effect of interest, we pool our previously defined k groups and use a local linear regression with a triangular kernel. We obtain an optimal bandwidth following Calonico et al. [2014]. Our empirical specification is the following:

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

In Equation 1, Y_{ik} is a dummy variable that denotes graduation for student i in group k. S_i is our running variable and denotes the score in the admission exam. We center the running variable by the group-specific admission cut-off 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. We estimate this specification and one that includes cut-off school fixed effects; our results remain the same. In addition, in Appendix K we show that our results are not sensitive to restricting the sample to groups k with low or high cut-offs c_k.

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 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 process. If there were manipulation, we would expect to observe bunching on the density of the running variable just above the admission cut-offs. Figure 2 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 2: Continuity test



As additional evidence supporting the validity of the design, Figure 3 shows that other predetermined covariates such as gender and GPA do not vary discontinuously at the cut-offs. We include estimates and standard errors in Appendix F.

Figure 3: Predetermined covariates

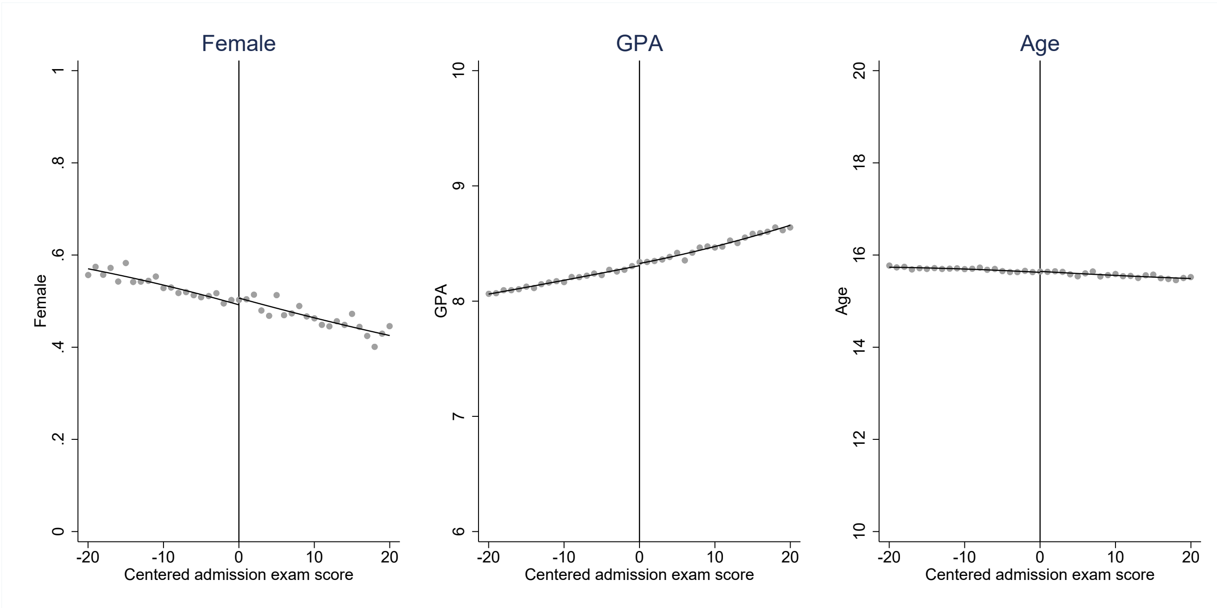
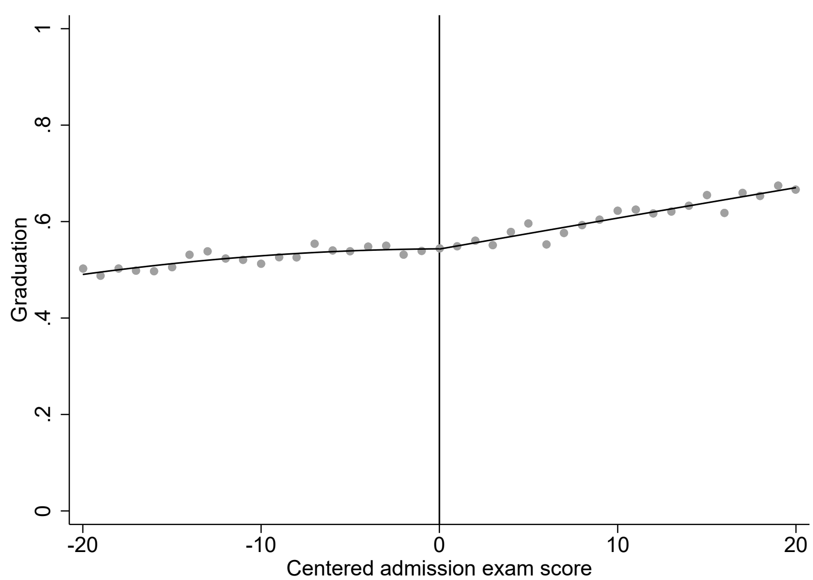


Figure 4 shows a graphical representation of the effect of marginal admission to an elite school on gradutaion without considering heterogeneity. Elite schools do not affect graduation for students marginally admitted to them. We show the estimated parameter $\hat{\gamma}$ and its standard error in Appendix I. The parameter is close to zero and is not statistically significant.

Figure 4: Elite schools effect on graduation



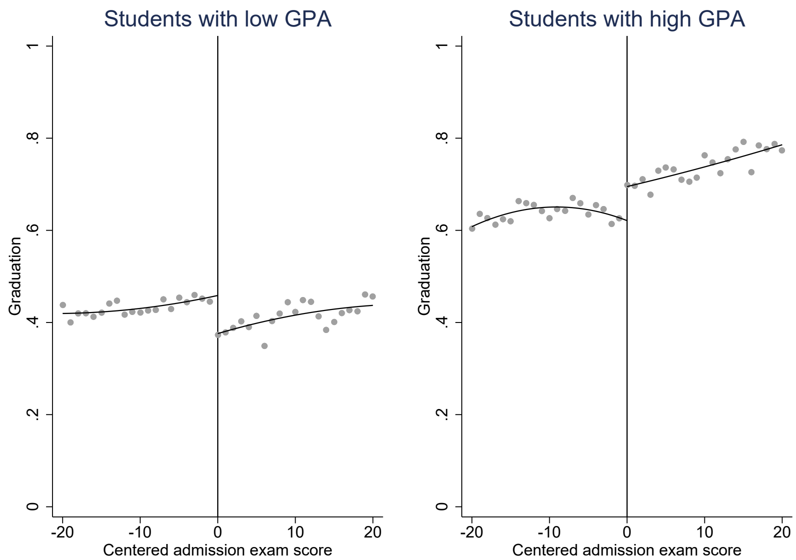
4.2 Heterogeneity by GPA

Students at the elite schools' admission cut-offs can be heterogeneous in other characteristics that affect graduation. For example, they can have high or low GPAs. Borghans 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 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 test captures IQ while GPA captures effort. Then, exploring our heterogeneity of interest would be equivalent to differentiating the effect of elite schools between high-ability low-effort students and high-ability high-effort 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 could be hard working or not. To the extent that graduating from an elite school requires you not only to have high ability but also to be hardworking, we would expect differentiated effects.

Figure 5 shows that the effect of marginal admission to an elite school on graduation is heterogeneous by previous GPA. It is negative (8 percentage points) and significant for students with below-median GPA, and it is positive (7 percentage points) and significant for students with above-median GPA. We include point estimates and standard errors in Appendix I. When we group high and low GPA students, the two effects cancel out and we get the results in Figure 4. We take these results as evidence that elite schools require a combination of ability and other skills that GPA better measures for a student to benefit from them (in terms of a higher graduation probability).

Figure 5: Elite school admission and graduation by GPA



Complementing our previous results, we perform three robustness checks. First, 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 Table 4, we show that our previous results are unchanged by this alternative definition of high and low GPA students.

Table 4: High and low within middle school GPA

	(1)	(2)
	Low	High
RD Estimate	-0.089***	0.066***
	(0.014)	(0.014)
N	22,673	21,932

Standard errors in parenthesis

Second, we use the residuals of regressing GPA on the admission exam score and an additional low-stakes standardized exam students take at the end of middle school to define high and low GPA students. We do this to isolate the skills GPA measures from those already accounted for by standardized exams. We show in Table 5 that our heterogeneous results remain almost identical. We interpret this as evidence that the additional skills GPA captures are driving our heterogeneous results by GPA.

Table 5: High and low residuals

	(1) Low	(2) High
RD Estimate	-0.067***	0.063***
	(0.015)	(0.016)
N	21,011	15,799

Standard errors in parenthesis

Third, we also explore heterogeneity by performance in the additional low-stakes standardized exam. Our results in Table 6 show no heterogeneous effect in this case. This last robustness check aims to show that GPA is more than just another measure of the same latent skill and discard pure noise reduction as a potential explanation behind our results.

Table 6: High and low low-stakes standardized exam

	(1) Low	(2) High
RD Estimate	-0.024	0.017
	(0.022)	(0.015)
N	10,039	18,960

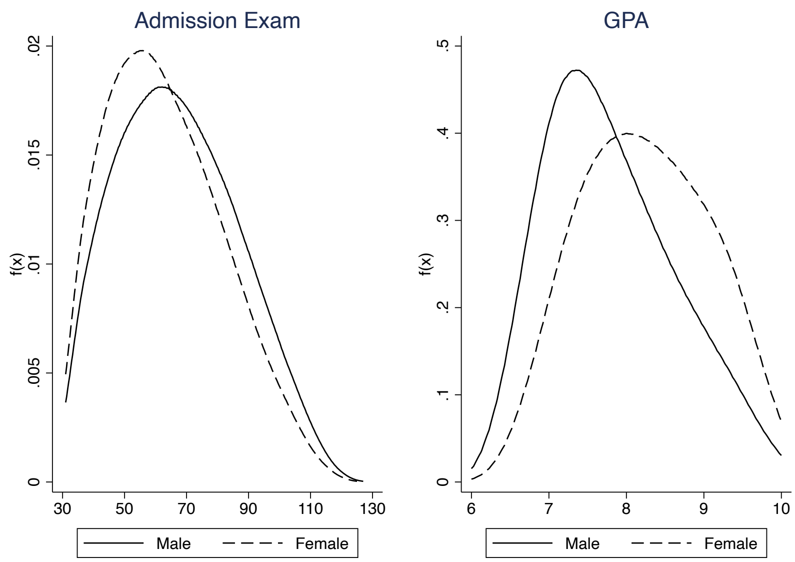
Standard errors in parenthesis

In Appendix K 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.

4.3 Heterogeneity by Gender

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 but that there may be gender differences in performance under competitive pressure. If this is the case, assigning students to elite schools based only on performance in an admission exam could be limiting females' access to them. Further, if females do have the skills required to benefit from elite schools, such an admission rule could increase mismatch and affect the graduation rate.

Figure 6: Admission exam score and GPA by gender



Consistent with previous research, our data shows that males score higher in the admission exam score, while females have higher GPAs (Figure 6). Furthermore, Figure 7 shows that at every quintile of the admission exam score distribution, females have higher GPAs than males. In the last section, we showed that the effect of elite schools on the graduation probability depends on previous GPA. Since females have higher GPAs and, arguably, more of the skills needed to graduate from an elite school, we would expect to also observe heterogeneous effects by gender.

Figure 7: Admission exam score, GPA, and gender

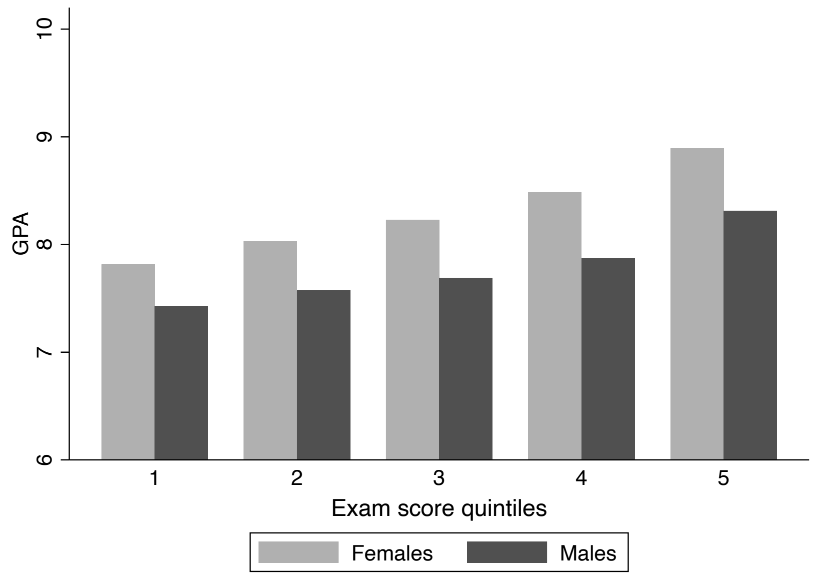
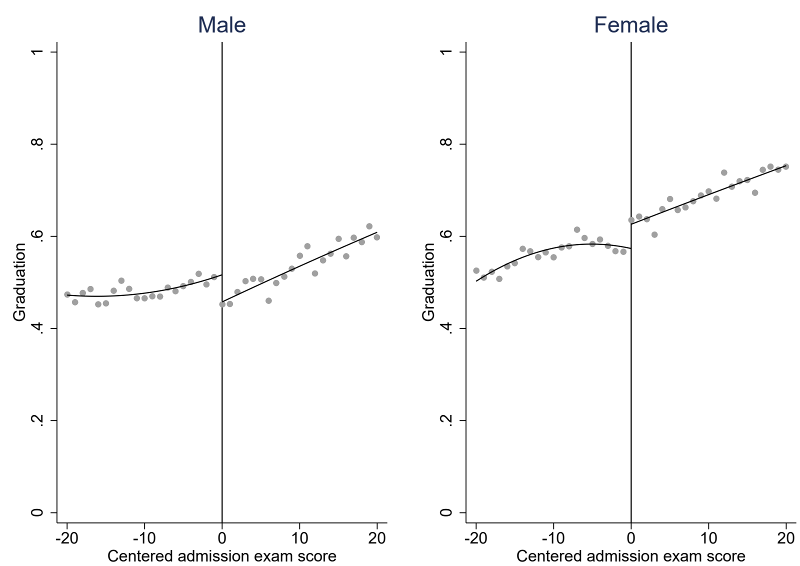


Figure 8 shows the results of implementing an RDD separately for males and females. The effect for males is almost identical (decrease of 6 percentage points) to the effect for students with below-median GPA, while the effect for females almost replicates (an increase of 6 percentage points) the effect for students with above-median GPA. We include point estimates and standard errors in Appendix I.

Figure 8: Elite school admission and graduation by gender



4.4 GPA and Gender

To further understand the source of heterogeneity in our treatment effects, we follow Gerardino et al. [2017] and use propensity score weighting to keep balance in other observable characteristics while doing a particular RDD subgroup analysis. Specifically, we balance gender while estimating heterogeneity by GPA and balance GPA when estimating heterogeneity by gender. We obtain two main results from this exercise (Table 7). First, when we balance gender, we still observe heterogeneous effects between high a low-GPA students, although the difference in effect sizes is smaller. Second, when we balance GPA, there are no longer differences in the effect of marginal admission between males and females.

Table 7: RDD estimates using propensity score weighting

	(1) Gender balanced	(2) GPA balanced
Low GPA	-0.052***	
	(0.011)	
High GPA	0.038***	
	(0.013)	
Male		-0.021
		(0.013)
Female		0.008
		(0.012)
Difference	.091***	.029

Standard errors in parenthesis

We interpret these results as evidence that the skills GPA captures are the main driver of our heterogeneous treatment effects by gender. Our differential gender effects come from females having higher GPAs than males at all percentiles of the standardized admission exam, including the cut-offs.

Overall, the results of our RDD analysis tell us two facts. First, admission to elite schools increases the graduation probability for students with enough of the skills required to graduate from them, and GPA is better capturing these skills. Second, the current admission policy limits females' access to elite schools even though they could potentially benefit the most from them (in terms of higher graduation probabilities).

5 Counterfactual Admission Policy

Motivated by our RDD results, we examine the effects of a counterfactual admission policy wherein the central planner puts equal weight on the admission exam score and GPA when defining the priority index of elite schools. The priority index of non-elite schools does not change and remains using the admission exam score.[9] Because of concerns regarding differential grading standards between middle schools, we also study a counterfactual where instead of using GPA as an additional input, the central planner uses within middle school percentile rank by GPA in the priority index of elite schools. Our results are not sensitive to this change. In this section, we show the counterfactual using GPA, and we include the results using middle school percentile rank by GPA in Appendix M.

In terms of the matching algorithm, in the counterfactual, elite schools have a priority index different from non-elite schools. This change is equivalent to letting the centralized system use the more general Student Proposing Deferred Acceptance (SPDA) algorithm that allows different schools to have different priority indexes. Thus, in our counterfactual, the matching algorithm is a more general case of the previously implemented, which does not affect its theoretical properties.

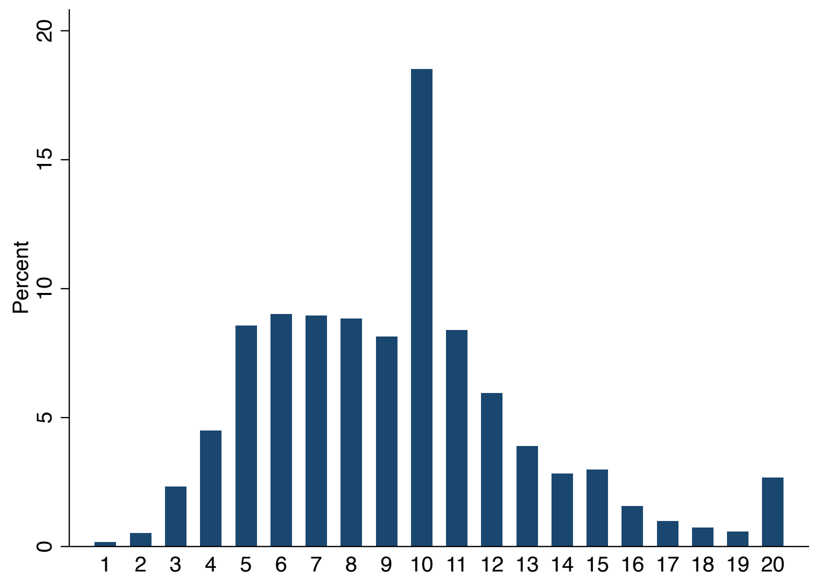
The primary assumption we make when analyzing the effect of our counterfactual policy is that students' ROLs do not change when priorities change. There are some cases when the change in priorities could affect the ROLs. One case considers that students could be strategic when choosing their ROLs. In 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. We believe that, in our context, students are not strategic for two reasons.

First, the SD and SPDA algorithms are strategy-proof when the length of students' ROLs is unrestricted [Haeringer and Klijn, 2009]. Although the Mexican system con-

[9] Our results are not sensitive to the central planner putting equal weight on the exam score and GPA in the priority index of elite and non-elite schools. We include these results in Appendix L.

strains the length of the ROLs to 20, only 2.7% of students submit a ROL of the maximum length. In Figure 9, we show the distribution of ROLs lengths in our data. Since the constraint does not appear to be binding, the strategy-proof theoretical property likely holds in practice. That is, students truthfully report their preferences as their ROLs without considering admission probabilities.[10]

Figure 9: ROLs length in 2007



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 can be more uncertain about their admission outcomes if schools use a priority index unknown to them when choosing their ROLS. This is the case in Mexico City, since 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

[10]Abdulkadiroğlu et al. [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 in favor of truthful revelation of preferences is that in practice, only 20% of students rank 12 schools.

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. 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. 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) at schools are small.

We estimate a flexible graduation model to obtain a relationship between students' characteristics and their graduation probability (Equation 2). We use a graduation model because our counterfactual admission policy affects students, for which our RDD estimates may not be informative. For instance, students beyond the margin of admission to an elite school.

We allow for sub-system specific model parameters so individual-level characteristics can differentially affect graduation probabilities from different schools. The dependent variable Y is a binary variable that equals one if student i graduated from a high school in sub-system s, and zero if not. The independent variables (vector x) are the score in the admission exam, middle school GPA, gender, age, and a constant. Notice that the constants α_s in Equation 3 capture sub-system-specific effects on the graduation probability.

$$P_s(x) = P_s[Y = 1 \mid X = x] = E_s[Y \mid X = x] \text{ , where } j \in \{1, ..., 9\} \tag{2}$$

$$P_s(x) = G(\alpha_s + x'\beta_s). \tag{3}$$

Equation 3 provides a mapping between student characteristics and the probability of graduation from sub-system s. The mapping is defined by the parameters α_s, β_s and the link function G, which we assume to be the logistic distribution.

Besides this first specification, we include in vector x control variables for some commonly unobservable attributes that can affect the graduation probability and be correlated with the included regressors. This set of additional controls are motivated by Dale and Krueger [2014] empirical specification, which takes advantage of the information revealed in college application lists. To include measures of aspirations or motivation, we add controls for the number of elite schools in students' ROLs, the length of their ROLs, and the average quality of the schools in their ROLs.[11] This is the specification we use to predict graduation outcomes in the counterfactual.

Because our graduation model relies on functional form and distributional assumptions, we perform a model validation exercise. For our model validation, we use the graduation probabilities predicted by our model in the baseline and perform the RDD analysis from the previous section using these predictions as the outcome. We find that our model predictions reproduce the main patterns of our RDD results. First, there is no average effect of marginal admission to an elite school. Second, there is a negative effect for below-median GPA students, and a positive effect for above-median GPA students. Third, there is a negative effect for males and a positive effect for females. We include the validation figures and tables in Appendix O.

Our counterfactual assigns some students to different schools than their initial assignment. For example, consider a student assigned to a school in sub-system s in the baseline who is assigned to a school in sub-system s' in the counterfactual. To calculate her graduation probability at the new sub-system, we use the mapping from student characteristics to the graduation probability we previously obtained for sub-system s'. The counterfactual probability of graduation for this student follows Equation 4.

$$\hat{P}_{s'}(x) = G(\hat{\alpha}_{s'} + x'\hat{\beta}_{s'}) \tag{4}$$

Notice that an implicit assumption in this exercise is that the parameters α_s and β_s do not change in the counterfactual. Consider the case where these parameters capture fixed sub-system characteristics such as infrastructure or quality of teachers. Then, the counterfactual is changing the students' characteristics that interact with these attributes (i.e., match effects). A more complex case is when α_s and β_s also capture the effect of the average peer quality on a student graduation probability. Even under

[11] 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 schools' cutoffs listed in the ROL.

this case, our counterfactual remains informative if the average peer quality at different sub-systems 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 the elite sub-systems have higher GPAs but lower admission exam scores.

5.1 Results

Our counterfactual exercise results in a different allocation of students across schools. In Table 8, we show the reallocations across elite and non-elite schools. In general, most of the students remain in their initial type of school. Importantly, our counterfactual exercise still considers students' choices and only moves students to other schools if they are part of their ROLs and are ranked in nearby positions as the schools of initial assignment.

Table 8: Baseline and counterfactual assignment

	Counterfactual		
	Non-Elite	Elite	Total
Non-Elite	152,117	9,317	161,434
	94%	6%	
Elite	8,930	42,220	51,150
	17%	83%	

We next investigate if our counterfactual has some consequences in the gender composition of students assigned to elite schools. Table 9 shows that our policy increases the share of female students assigned to elite schools by nine percentage points. This change occurs because females demand elite schools in their ROLs, but the current admission policy limits their access. By adding weight to GPA, a measure in which females outperform males, more females gain access to elite schools. Table 9 also shows that our counterfactual increases elite schools' graduation rate by six percentage points. The graduation rate increases because the counterfactual assigns more high GPA students to elite schools, and these students have more of the skills needed to graduate from them.

Table 9: Changes in composition and graduation rates

	Baseline	Counterfactual	Diff
Elite			
Female	45.12%	53.32%	8.21
Graduation	64.58%	70.71%	6.14
Non-Elite			
Female	50.88%	48.50%	-2.37
Graduation	45.88%	44.72%	-1.16

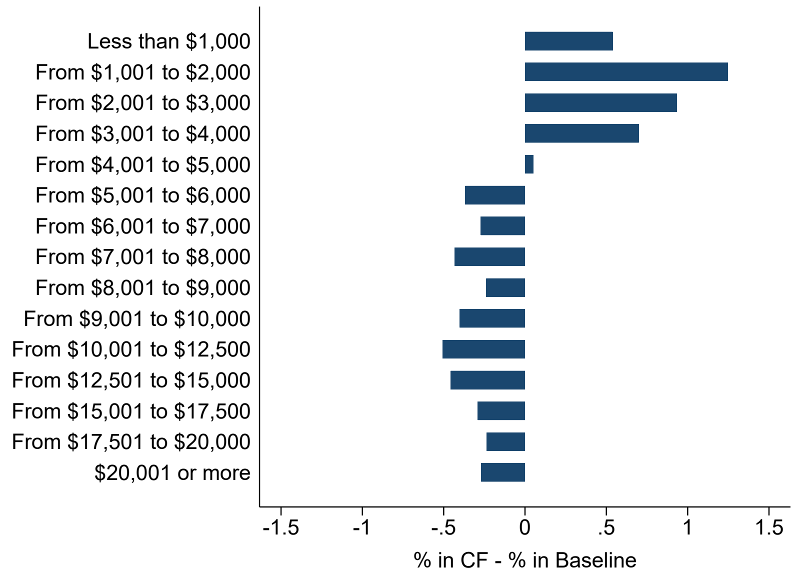
Table 10 shows that the overall graduation rate in the system is mostly unchanged (less than a one percentage point increase). In addition, in Table 10 we show the results for two subgroups of students: the placed and the displaced. Placed students are those who transition from non-elite to elite schools. Displaced students are those who transition from elite to non-elite schools. Comparing the initial with the counterfactual assignment, the graduation rate for the displaced students increases by seven percentage points, and the graduation rate for the placed students increases by six percentage points. We take this as evidence of mismatch in the initial allocation of students.

Table 10: Graduation of placed and displaced students

All		Displaced		Placed	
Baseline	CF	Baseline	CF	Baseline	CF
50.6%	51.3%	40.4%	47.1%	68.1%	74.2%

In addition, in Figure 10, we show that our counterfactual increases the share of low-income 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 be partially explained by high-income students having access to private exam-preparation institutions that are costly. Adding weight to GPA makes the admission exam score relatively less important and increases low-income students' access to elite schools. Both low and high-income students demand elite schools, but low-income students have less access to them in the current system.

Figure 10: Changes in the income composition of students at elite schools



5.2 Ex-ante Students' Welfare

So far we showed that under the new priority ordering more females and low-income students are assigned to elite schools while the graduation rate also increases. These may be desirable outcomes from the point of view of a central planner. However, students may prefer the baseline allocation if the new priorities assign them to schools that are farther away from their homes and they highly value distance to school. For this reason, in this section we focus our attention on students welfare gains and loses induced by the policy change. Furthermore, in addition of measuring the overall efficiency of the system, we study who gains and loses from our proposed admission policy.

To approximate effects on students' ex-ante welfare, we first use the position in the ROL a student is assigned. Since students choose schools based on their utilities, gaining admission to a highly ranked option provides them higher utility. In Table 11, we show that, on average, there are no changes in the position in their ROLs students are assigned. However, when separating males and females, we can see that the share of females assigned to their first option increases while the share of males assigned to their first option decreases. We interpret these results as a welfare trade-off between females and males.

Table 11: Position in ROL

	All		Female		Male	
	Baseline	CF	Baseline	CF	Baseline	CF
1	40.43%	40.46%	35.02%	38.58%	45.71%	42.35%
2	14.04%	14.03%	13.92%	13.89%	14.15%	14.16%
3	10.01%	10.09%	10.61%	10.42%	9.43%	9.77%
4	8.28%	8.26%	9.21%	8.54%	7.37%	7.98%
5	7.21%	7.09%	8.07%	7.31%	6.37%	6.87%

A limitation of the results in Table 11 is that we cannot quantify how much males' and females' welfare change in the counterfactual. For example, it could be the case that females' welfare increases slightly while males' welfare decreases by a lot, since these quantities depend on males and females' cardinal preferences. To complement our welfare analysis with a measure with cardinal value, we estimate students' preferences and scale the indirect utility by the distance coefficient. In this way, we can measure cardinal students' welfare in miles.

Define the indirect utility U_{ij} student i gets from school j as follows:

$$U_{ij} = \underbrace{x_j'\beta + \xi_j}_{\delta_j} + x_j'\Gamma z_i - D_{ij} + \epsilon_{ij} \tag{5}$$

$$U_{ij} = \underbrace{\delta_j + x_j'\Gamma z_i - D_{ij}}_{V_{ij}} + \epsilon_{ij} \tag{6}$$

In Equation 5, x_j is a vector of school characteristics that includes an elite school indicator and the previous year's admission cut-off. We also add an unobserved school characteristic denoted by ξ_j. In vector z_i, we include individual-level characteristics: a standardized ability index, GPA, gender and age. We also include the distance from a student middle school to each of the available high schools (D_{ij}). We normalize the distance coefficient to one. In equation 6, we group individual invariant regressors in the coefficients δ_j that capture school fixed-effects.

We follow Beggs et al. [1981] and estimate preferences using a Rank-Ordered Logit. Denote the length of a student ROL_i as K_i. Then, the probability that student i chooses ROL_i is:

$$P[ROL_i = (j_1, j_2, ..., j_{K_i}) \mid x_j, z_i, D_{ij}; \theta] = \frac{exp(V_{ij_1})}{\sum_{l \in J} exp(V_{il})} \times ... \times \frac{exp(V_{ij_K})}{\sum_{l \in J \setminus \{j_1, ..., j_{K_i - 1}\}} exp(V_{il})}. \tag{7}$$

The log-likelihood of the observed ROLs in the data is:

$$L(\theta) = \sum_{i}^{N} logP[ROL_i = (j_1, j_2, ..., j_{K_i}) \mid x_j, z_i, D_{ij}; \theta], \tag{8}$$

where all the model parameters are grouped in vector θ.

Even after obtaining estimates of the preferences' parameters, we still do not observe individual-level indirect utilities. However, we can use our estimated choice model to calculate the expected indirect utility a student obtains from her assignment in the baseline and her assignment in the counterfactual.

We do not observe U_{ij}, but we can take its expectation conditional on all we observe. To calculate this conditional expectation we follow [Abdulkadiroğlu et al., 2017]. Notice that the observed ROLs impose restrictions in the space where ϵ_{ij}. Following their definition of welfare, the following is the our conditional expectation of interest:

$$E[U_{ij} \mid ROL_i, z_i, x_j, d_i; \theta] = \begin{cases} E[U_{ij} \mid U_{ir_{i1}} > \cdots > U_{ir_{ik-1}} > U_{ij} > U_{ir_{ik+1}} > \cdots > U_{ir_{iK_i}}], & \text{if } j \text{ is kth} \\ E[U_{ij} \mid U_{ir_{i1}} > \cdots > U_{ir_{ik}} > \cdots > U_{ir_{iK_i}} > U_{ij}], & \text{if } j \text{ is not ranked.} \end{cases}$$

In our case, this simplifies to:

$$E[U_{ij} \mid ROL_i, z_i, x_j, d_i; \theta] = V_{ij} + E[\epsilon_{ij} \mid ROL_i, z_i, x_j, d_i; \theta],$$

and as derived by Abdulkadiroğlu et al. [2020], this conditional expectation has closed form.

Define the average welfare produced by matching μ as:

$$W(\mu) = \frac{1}{I} \sum_{i} E[U_{i\mu(i)} \mid V_{ij}, ROL_i],$$

where I is the total number of students and $\mu(i)$ is a function that indicates the school to which student i is assigned.

Denote $\mu_{base}(i)$ and $\mu_{CF}(i)$ as functions that indicate to which school j student i is assigned in the data and in the counterfactual, respectively. We calculate student welfare in the baseline as:

$$W(\mu_{base}(i)) = E\left[U_{i\mu_{base}(i)} \mid V_{ij}, ROL_i\right]. \tag{9}$$

To calculate welfare in the counterfactual we use the assignments we obtained after implementing the SPDA matching algorithm under the new priorities. Student welfare in the counterfactual is:

$$W(\mu_{CF}(i)) = E\left[U_{i\mu_{CF}(i)} \mid V_{ij}, ROL_i\right]. \tag{10}$$

Consistent with our results in Table 11, the students' ex-ante welfare distribution does not change in the counterfactual (Figure 11). This can be explained by the SD mechanism being pareto efficient and the SPDA mechanism being pareto efficient within the set of stable matches. But as we also know from Table 11, there is heterogeneity in the welfare effects by gender. Figure 12 shows that, for the students that experience a change in their allocation, the welfare distribution is shifted to the right for females while shifted to the left for males. Average female welfare increases 2.5 miles, and average male welfare decreases 2.0 miles. These results show that our counterfactual induces a welfare trade-off between males and females, and it does not disproportionately affect one group or benefit another.

Figure 11: Change in welfare

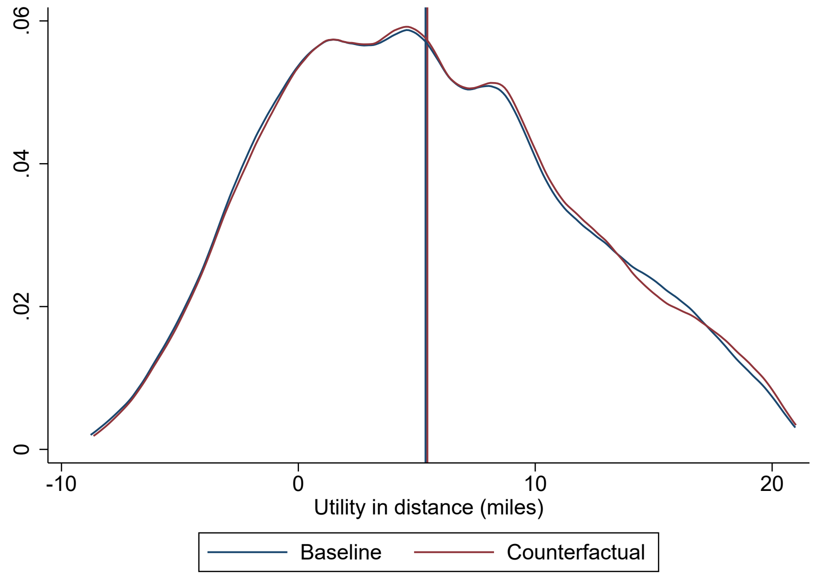
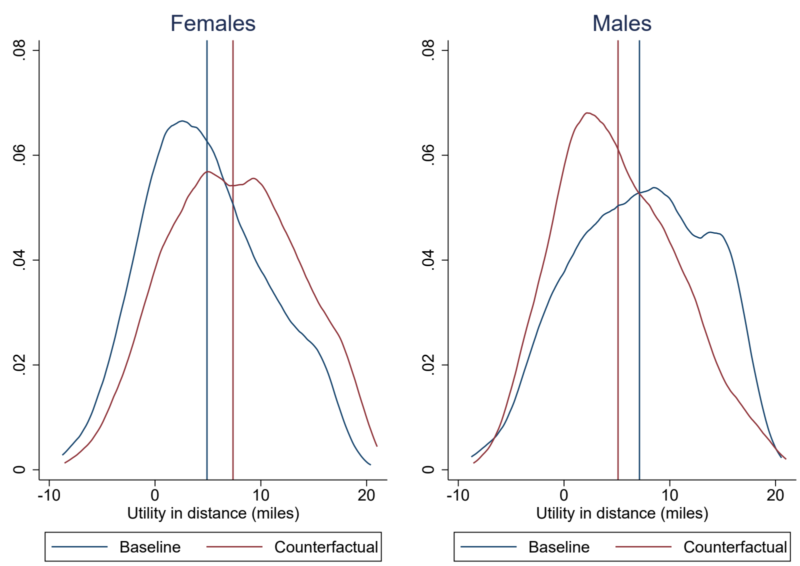
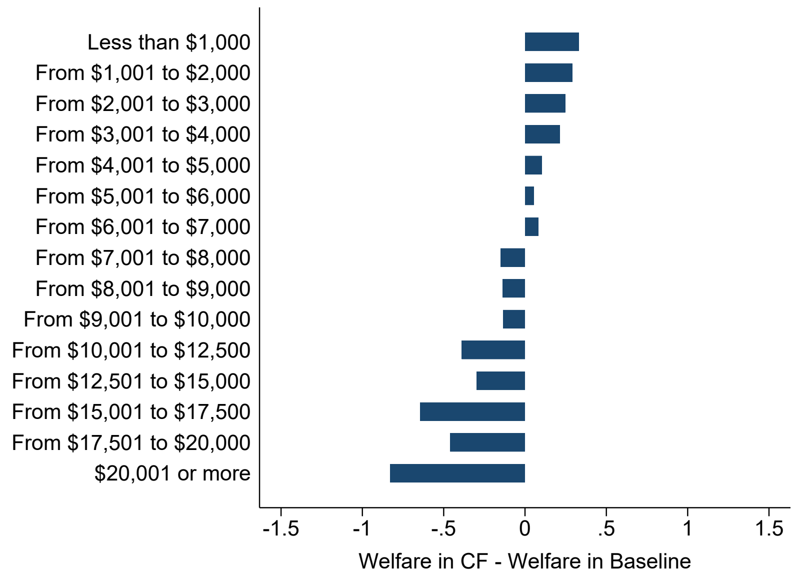


Figure 12: Change in welfare by gender



Lastly, as we show in Figure 10, our counterfactual increases low-income students' access to elite schools. If elite schools are valuable for these students, then we would expect an increase in their welfare. In Figure 13, we show that this is the case. The welfare of low-income students increases while the welfare of high-income students decreases. The direction of the effect changes at a family income of 7,000 pesos. Importantly, most of the students (79%) come from households with family incomes of less than or equal 7,000 pesos.

Figure 13: Change in welfare by income



6 Conclusions

The way a priority ordering is defined in a centralized education system can affect equity of access and graduation rates. The relevance of this choice is highlighted when priorities include skill measurements, and students have heterogeneous skills. In this case, a given priority ordering could match students without the skills needed to graduate with the most academically demanding schools. Furthermore, school priorities play an essential role when evaluations of centralized education systems go beyond efficiency measures based on revealed preferences and consider other policy-relevant outcomes such as equity of access and graduation rates.

We exploit the case of the centralized high school admission system in Mexico City, where priorities are based on a standardized admission exam, to study the effects of including the information contained in GPA as part of elite high schools' priority index. 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 educational success. We first show that students marginally admitted to elite schools experience an increase in their graduation probability only when they have above-median middle school GPA. In addition, the effect is also positive only for females, partially because they have higher GPAs than males. Our first set of results motivate the importance of considering heterogeneity in skills when studying how elite schools affect the graduation probability even for students at the margin of admission.

Guided by these results, we then study the effects of a counterfactual admission policy where the central planner puts equal weight on the admission exam and GPA in elite schools' priority index. Because GPA levels are not standardized, we also consider a case where elite schools' priority index includes middle school percentile ranking by GPA instead of GPA. Our results are not sensitive to this change. Our counterfactual results are three. First, more females and low-income students gain access to elite schools. Second, the graduation rate from elite schools increases by six percentage points. Third, the system's average ex-ante students' welfare remains the same, but females' and low-income students' welfare increases while males' and high-income students' welfare decreases. Winners welfare increases by approximately the same quantity as losers welfare decreases, which indicates a welfare trade-off.

A limitation of our paper is that our counterfactual admission policy could induce additional behavioral responses that we are not currently considering. For example, it could change 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, then our effect on the elite schools' graduation rate would be a lower bound.[12] Another possibility is that middle school grades could increase not because of students' higher study effort but because of teachers' changing grading standards, leading to grade inflation. However, as we showed in the analysis, our results do not vary if, instead of GPA, the elite schools' priority index uses middle school percentile ranking by GPA, which is not affected by grade inflation. In general, depending on their primary concern, policymakers could flexibly choose how to incorporate the information contained in GPA instead of throwing that information away.

From a policy perspective, our results indicate that using the information contained in GPA when defining admission priorities to elite over-subscribed schools can benefit the centralized system in Mexico City. More broadly, other centralized systems like

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

the one studied here in that they rely on a unique standardized test to define school priorities could also benefit from adding some weight to the skills better measured by grades. Examples of such systems are the centralized education systems in Romania, Kenya, and the college admission system in China.

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

Abdulkadiroğlu, A., Pathak, P. A., Schellenberg, J. and Walters, C. R. [2020], 'Do parents value school effectiveness?', *American Economic Review* **110**(5), 1502–39.

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.

Becker, S. O., Egger, P. H. and Von Ehrlich, M. [2013], 'Absorptive capacity and the growth and investment effects of regional transfers: A regression discontinuity design with heterogeneous treatment effects', *American Economic Journal: Economic Policy* **5**(4), 29–77.

Beggs, S., Cardell, S. and Hausman, J. [1981], 'Assessing the potential demand for electric cars', *Journal of econometrics* **17**(1), 1–19.

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.

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.

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.

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.

Heckman, J. J., Humphries, J. E. and Kautz, T. [2014], *The myth of achievement tests: The GED and the role of character in American life*, University of Chicago Press.

Hsu, Y.-C. and Shen, S. [2019], 'Testing treatment effect heterogeneity in regression discontinuity designs', *Journal of Econometrics* **208**(2), 468–486.

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

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.

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.

Rokkanen, M. A. [2015], 'Exam schools, ability, and the effects of affirmative action: Latent factor extrapolation in the regression discontinuity design'.

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

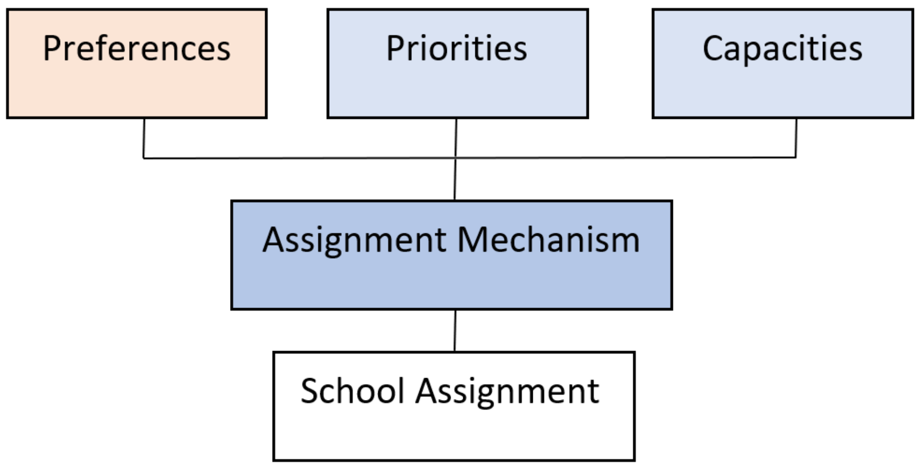
Stinebrickner, R. and Stinebrickner, T. R. [2006], 'What can be learned about peer effects using college roommates? evidence from new survey data and students from disadvantaged backgrounds', *Journal of public Economics* **90**(8-9), 1435–1454.

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

A Centralized education markets

Figure 14 shows the different components of a centralized education market. Examples of markets that follow this structure are: Boston, Cambridge, Chicago, Denver, Miami, New Orleans, NYC, San Francisco, Washington DC, Mexico City, Romania, Ghana, and Kenya.

Figure 14: Structure of a centralized education market



B The admission exam

Table 12: 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

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 12 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.

C SPDA mechanism

For the SPDA mechanism, schools can have different priorities over the students, and each student defines her ROL. The matching algorithm is as follows [13]:

- Step 1: Schools receive applications from students who ranked them first in their ROL. Schools that received fewer applications than their capacity hold on to these applications. Each school j that received more applications than its capacity q_j temporarily holds on to the q_j applicants with the highest priority and rejects all others.

[13] We follow the notation in Luflade (2018).

- Step (k+1): For any $k \geq 1$, students who received a rejection notification at step k send an application to the school ranked next on their ROL. Schools then consider their total pool of applications: those just received and those held on at step k (if any). Schools that have fewer applications than their capacity hold on to these applications. Each school j with excess applications temporarily holds on to the q_j applicants with the highest priority and rejects all others.
- Stop: The algorithm stops after all students who received rejections have exhausted their list of acceptable schools. Schools formally admit applicants they hold on to at this stage.

When all the schools have the same priorities, the algorithm is equivalent to the Serial Dictatorship.

D Serial Dictatorship mechanism

All schools have the same priorities, 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 equivalent to an SPDA algorithm in which all schools have the same priorities.

E Descriptive evidence

Table 13 shows the results of estimating a linear probability model (LPM) of graduation for elite and non-elite schools. Regressors include a dummy variable that indicates if a student has an above-median GPA and the admission exam score. We also include controls for gender, age, and student preferences. For students at non-elite schools, we restrict the sample to students with a GPA of at least 7/10 and an admission score of at least 69/128. The reason for the sample restriction is that all students at elite schools have a GPA of at least 7/10 and the lowest admission score of a student admitted to an elite school is 69/128.

Table 13: Graduation

	(1)	(2)
	Elite	Non-elite
Above-median GPA	0.277***	0.200***
	(0.005)	(0.005)
Admission exam	0.069***	0.065***
	(0.003)	(0.006)
Mean graduation	0.646	0.589
Obs	54,652	40,502

Standard errors in parenthesis

F Predetermined covariates

Table 14 shows the point estimates and standard errors of estimating the effect of marginal admission to an elite school on predetermined covariates using a local linear regression with a triangular kernel. The point estimates are close to zero and not statistically significant.

Table 14: Predetermined covariates

	(1)	(2)	(3)
	Female	Poor	GPA
RD Estimate	0.011	-0.009	0.022
	(0.010)	(0.011)	(0.016)
N	49,784	37,664	43,238

Standard errors in parenthesis

G Density test for above and below median GPA

To show the validity of the design even after we split the sample into low and high GPA students, in Figure 15 and 16 we show evidence that in both subsamples there is no evidence of bunching in the running variable at the cut-offs.

Figure 15: Low GPA sample

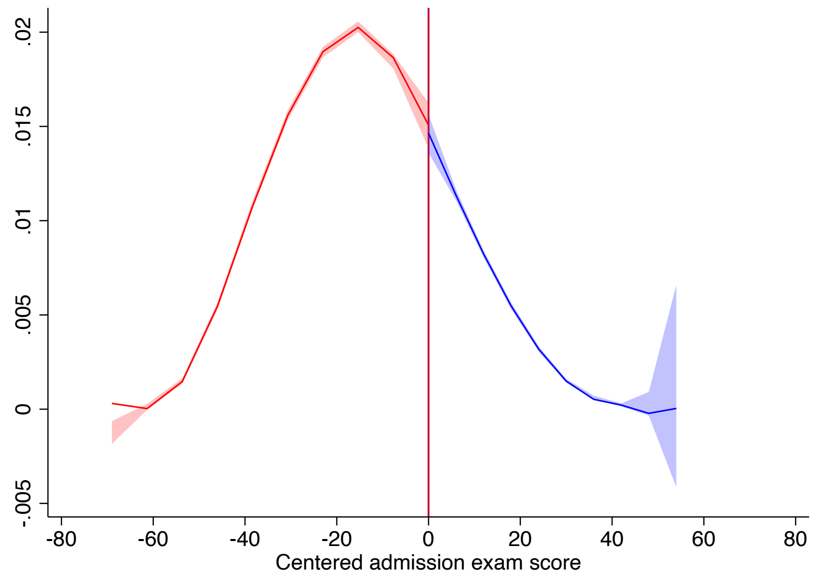
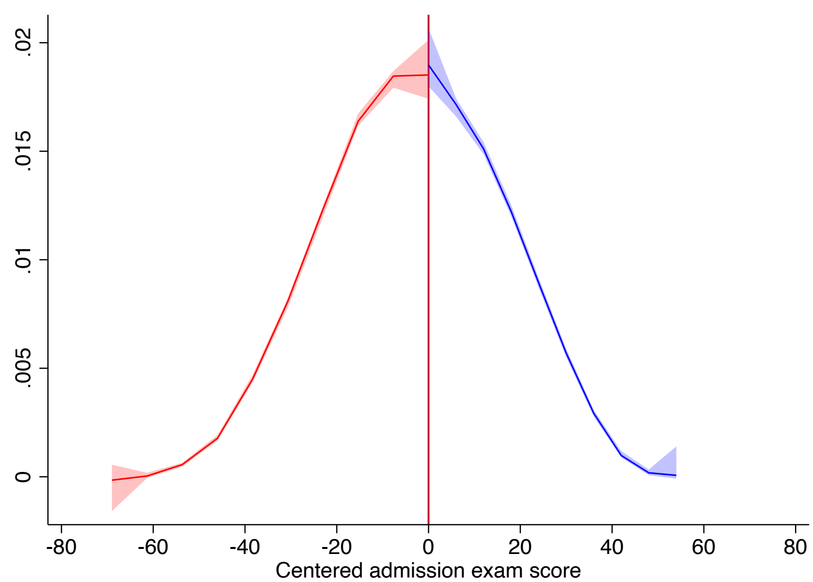


Figure 16: High GPA sample



H RDD example

Define the potential outcomes of attending an elite (Y_1) or a non-elite (Y_0) school, S is a continuous running variable (admission score), c is the elite school admission's cut-off, and G is a dummy variable that indicates high GPA.

$$Y_1 = \alpha_1 + \beta_1(S - c) + \theta_1 G + \nu_1$$
$$Y_0 = \alpha_0 + \beta_0(S - c) + \theta_0 G + \nu_0$$

Notice that $\theta_1 \neq \theta_0$

$$E[Y_1 \mid S = c, G = 1] - E[Y_0 \mid S = c, G = 1] = (\alpha_1 + \theta_1) - (\alpha_0 + \theta_0)$$
$$E[Y_1 \mid S = c, G = 0] - E[Y_0 \mid S = c, G = 0] = \alpha_1 - \alpha_0$$

If $\theta_1 > \theta_0$: the effect for high GPA students is larger than the effect for low GPA students.

I Estimates

Table 15 shows the point estimates and standard errors of estimating the effect of marginal admission to an elite school on graduation for different groups of students. For the estimation we use a local linear regression with a triangular kernel.

Table 15: Graduation, optimal bandwidth

	(1)	(2)	(3)	(4)	(5)
	All	Low GPA	High GPA	Males	Females
RD Estimate	-0.003	-0.081***	0.074***	-0.060***	0.064***
	(0.010)	(0.015)	(0.015)	(0.015)	(0.016)
N	49,784	19,489	18,797	21,495	18,371

Standard errors in parenthesis

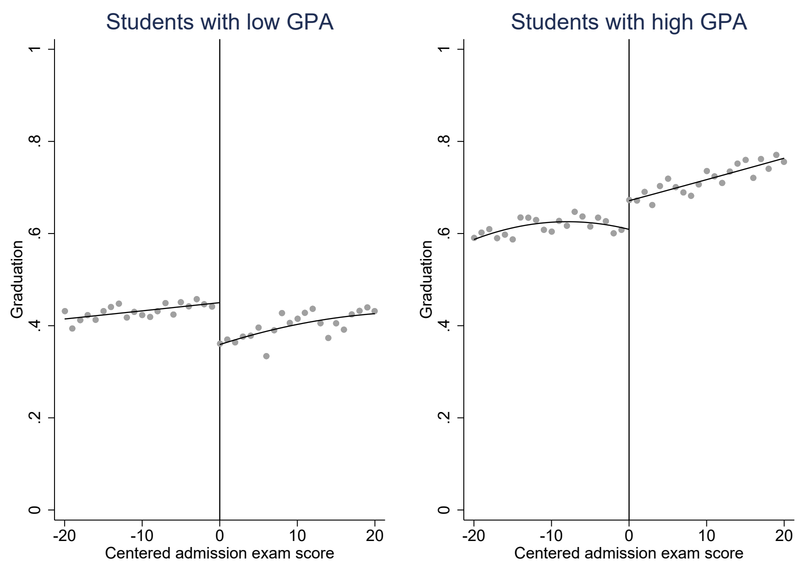
Table 16: Graduation, half the optimal bandwidth

	(1)	(2)	(3)	(4)	(5)
	All	Low GPA	High GPA	Males	Females
RD Estimate	0.008	-0.073***	0.083***	-0.062***	0.081***
	(0.014)	(0.023)	(0.022)	(0.021)	(0.024)
N	26,360	9,432	10,106	11,469	9,806

Standard errors in parenthesis

J Above and below-median within middle school GPA distribution

Figure 17: Elite school admission and graduation by GPA



K 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 graduation do not depend on elite schools having high or low cut-offs. Instead of pooling together our k groups, we separate this groups into low and high elite school cut-offs and repeat the analysis for each sub-sample.

Figure 18: Elite schools with low cut-off

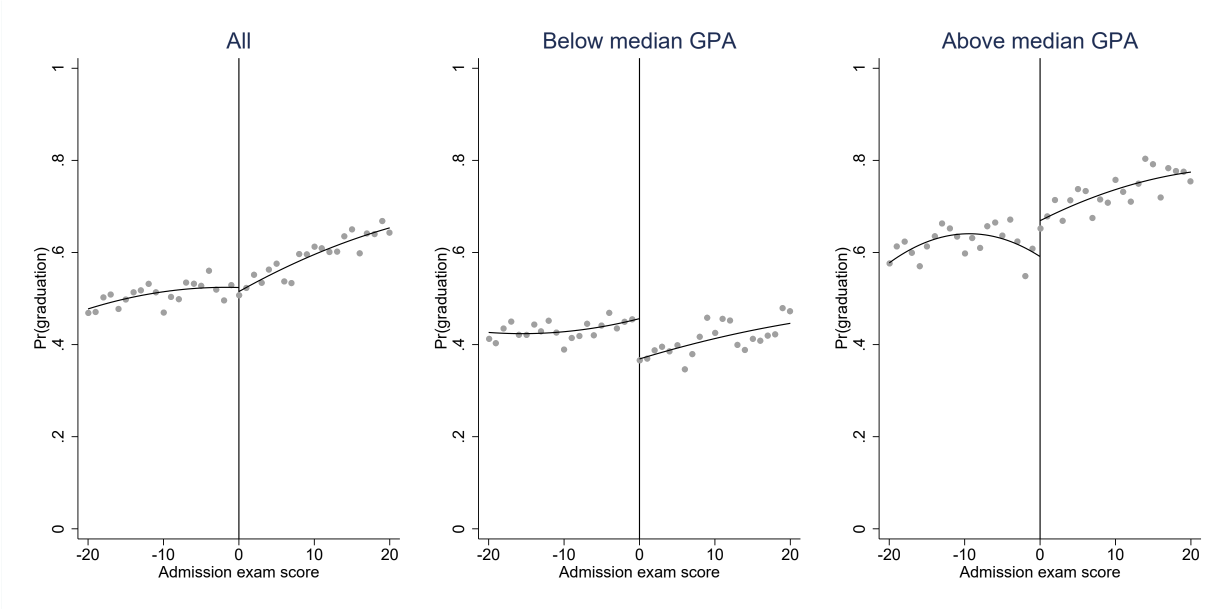


Figure 19: Elite schools with high cut-off

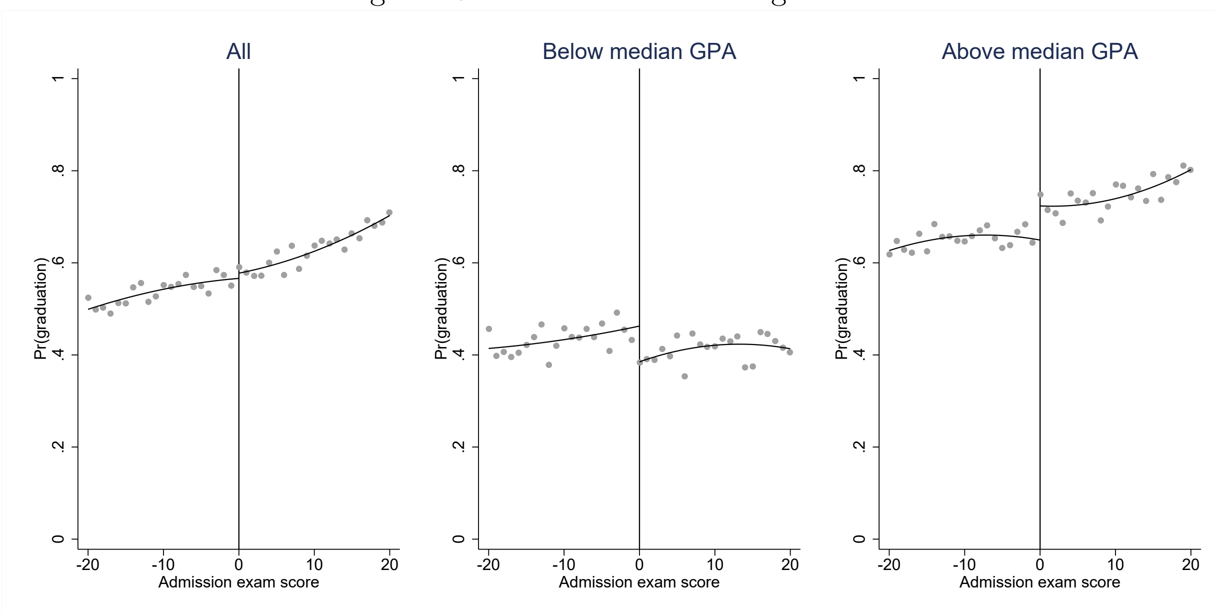


Figure 18 and Figure 19 show that our main results do not change when we only consider elite schools with high or low cut-offs. Marginal admission to an elite school does not affect graduation. But this effect depends on students middle school GPA, for students with below median GPA, the effect is negative, while for students with above median GPA the effect is positive.

L All schools use GPA

Table 17 shows the results of a counterfactual where the central planner puts equal weight on the admission exam score and GPA in the priority index of elite and non-elite schools.

Table 17: Robustness, all schools add GPA

	Initial	Counterfactual	Diff
Elite			
Female	45.12%	53.32%	8.21
Graduation	64.58%	70.71%	6.14
Non-Elite			
Female	50.88%	48.51%	-2.37
Graduation	45.88%	44.71%	-1.17

M Alternative priority structure

Table 18 shows the results of a counterfactual where the central planner puts equal weight on the admission exam score and students' within middle school percentile ranking by GPA in the priority index of elite schools.

Table 18: Robustness, middle school percentile ranking by GPA

	Initial	Counterfactual	Diff
Elite			
Female	45.12%	53.27%	8.16
Graduation	64.58%	70.02%	5.44
Non-Elite			
Female	50.88%	48.56%	-2.32
Graduation	45.88%	44.82%	-1.06

N Welfare example

- Students rank schools following their utilities:

$$U(r_1) > U(r_2) > ... > U(r_{10})$$

- $\downarrow$ welfare

  $Jose = \{r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}\}$ baseline

  $Jose = \{r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}\}$ CF

- $\uparrow$ welfare

  $Maria = \{r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}\}$ baseline

  $Maria = \{r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}\}$ CF

- Intensity of preferences determines how much Maria gains and how much Jose loses

- We can use observed ROLs to recover distribution of utilities

O Validation

For our model validation exercise, we repeat our RDD analysis using as an outcome our model-predicted graduation probabilities ($\hat{Y}$). Figure 20 shows that there is no effect of marginal admission to an elite school on $\hat{Y}$.

Figure 20: Model validation

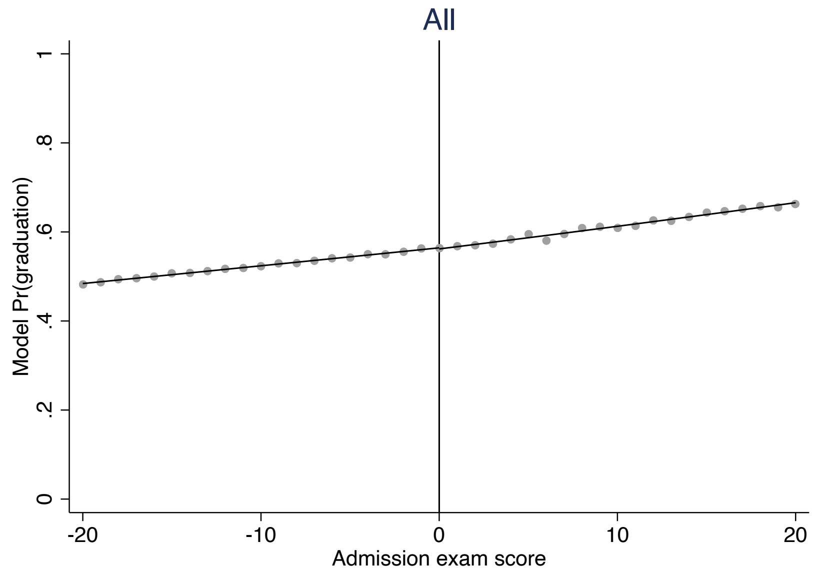


Figure 21 and Figure 22 show that our model also reproduces the heterogeneous effects by GPA and gender when we use $\hat{Y}$ as our outcome.

Figure 21: Model validation, GPA

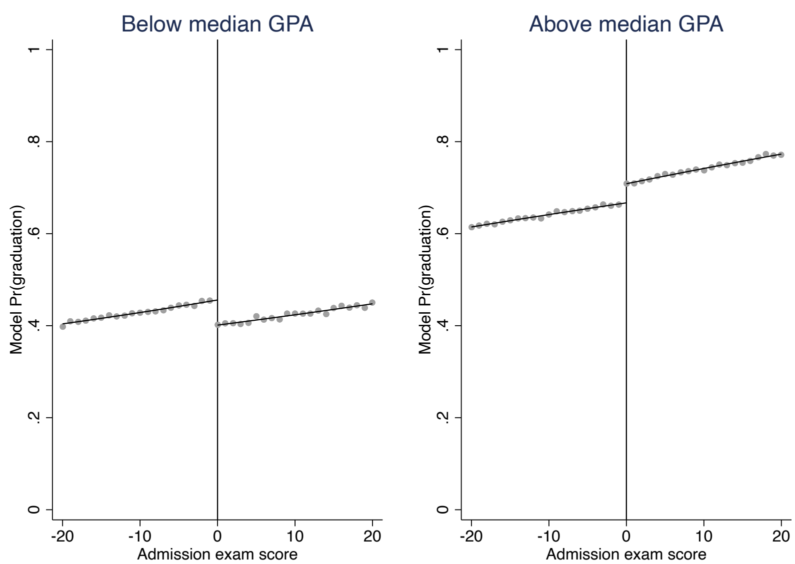
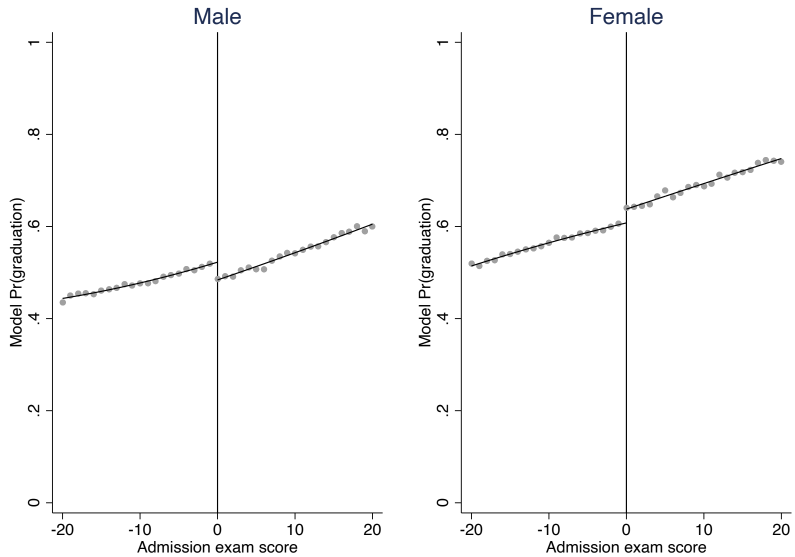


Figure 22: Model validation, gender



Lastly, 19 shows the point estimates and standard errors of our validation exercise. All the effects go in the same direction as the results using the data. However, the point estimates are slightly smaller in magnitude.

Table 19: Model Pr(graduation)

	(1)	(2)	(3)	(4)	(5)
	All	Low GPA	High GPA	Males	Females
RD Estimate	-0.003	-0.056***	0.042***	-0.038***	0.029***
	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)
N	49,784	17,826	28,401	21,495	25,077

Standard errors in parenthesis