School Choice, Mismatch, and Graduation

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Abstract

In all centralized education systems, some schools experience excess demand. A standard solution to the excess demand problem is to ration seats using admission priorities. This paper studies the effects of changing the priority structure in the centralized high school admission system in Mexico City. In this system, academically elite schools experience excess demand, and admission priorities are based on a standardized admission exam. The system ignores other skill measures such as Grade Point Average (GPA), which may better capture non-cognitive skills that are important for educational success. Using a Regression Discontinuity Design, we first show that marginal admission to an elite school decreases the graduation probability for students with below-median GPA and increases it for students with above-median GPA. Guided by this evidence, we then study the effects of a counterfactual admission policy wherein elite schools define a priority index that equally weights the admission exam score and GPA. In our counterfactual, more females and lower-income students are admitted to elite schools, and the graduation rate at elite schools increases eight percentage points. Our counterfactual also has effects on welfare. Females' welfare increases at the cost of males' welfare, and low-income students' welfare increases at the expense of high-income students' welfare. Overall, our findings show that including the information contained in GPA to define a priority structure improves equity of access, decreases mismatch, and increases graduation.

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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)*

Centralized education systems that assign students to public schools are rapidly expanding worldwide (Krussig and Neilson, 2021). 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, 2020). Since using prices as a rationing mechanism is not feasible in public education, policymakers define priority structures that assign a priority index to each student. Priorities solve the excess demand problem by providing an ordering in which students gain admission to schools. Typical components of priority indices are siblings, residential zones, lotteries, a standardized exam, and GPA.

In practice, there is significant heterogeneity in how current systems define priorities. Understanding the consequences of implementing a given priority structure is essential for several reasons. First, the inputs used to create a priority index within a system could affect the equity of access. For example, consider a scenario 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. In addition, a particular way to rank students 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 could result in low graduation rates due to mismatch.

In this paper, we explore these issues by exploiting 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 and non-elite. Elite high schools are more academically demanding and experience much higher demand than available seats. Both elite and non-elite schools use the same priority index.[1] We focus on the following question: Is the system ignoring valuable information that could be used to create better matches? For example, the system could benefit from broadening the priority index by also considering GPA. We center on GPA as a potential way 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, 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).

To answer our research question, we use the administrative records of all the participants in the centralized high school admission process in Mexico City in 2007. We complement the admission data by collecting official high school graduation records for all the students assigned to schools through the centralized process. Our data provide us with two advantages for the analysis. First, we have information on application and graduation for close to 300,000 students which allow us to explore rich heterogeneity without running into statistical precision problems. Second, our dataset includes all the information necessary to replicate the observed student-school matches in addition to information the system had available but did not use to define priorities. In particular, we have access to students' middle school GPA.

We divide the analysis into two parts. The first part serves to highlight 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 (e.g., elite schools). We begin 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. We leverage these admission cut-offs and implement 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 have high and low GPAs. We are able to estimate an RDD separately for students with above and below

[1] 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.

median GPAs thanks to our large number of observations. We find that elite schools decrease the probability of graduation by eight percentage points for students with below-median GPA. For students with above-median GPA, elite schools increase their probability of graduation by eight percentage points. The lack of an overall effect can be 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 better captured by GPA.

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 the one for students with high GPAs. Males experience a decrease in their graduation probability, while females experience an increase in their graduation probability. We explain these results by the fact that in our data, even though males have higher admission exam scores than females, females have higher GPAs than males.

In the second part of the paper, guided by the results of the RDD analysis, we 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 graduation model for each school. Our counterfactual admission policy changes the elite schools' priority index to equally weight GPA and the admission exam score. Non-elite schools remain using the admission exam score as their priority index. Under the new priority structure, we run a more general version of the assignment algorithm currently implemented that allows for different schools to have different priorities. We work under the assumption that students' application lists do not change in the counterfactual since the assignment algorithm remains strategy-proof regardless of the change in priorities. However, the change in priorities does affect the assignment of students to elite and non-elite schools.

Our counterfactual generates 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 discrete choice graduation model give us a mapping between students' characteristics and their probability of graduation. We combine the estimated parameters from our graduation model and the new students' characteristics allocated to each school to predict graduation in the counterfactual. Our results show that in the counterfactual, graduation from elite schools increases eight 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.

Lastly, we estimate students' preferences to explore the welfare effects of our counterfactual admission policy. 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. Our welfare effects are driven by females and low-income students gaining access to more preferred schools in their ROLs, while males and high-income students see less access to their top choices.

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). Yet, defining a priority structure is an integral part of the design in a centralized system. Krussig and Neilson (2021) review centralized education systems worldwide and highlight that the causes and consequences of implementing different priority structures are currently understudied. Shi (2020) and Abdulkadiroglu et al. (2021) are the more related papers to ours. Their focus is on finding optimal priority structures in centralized education systems. However, they do not look at students' educational outcomes. As Agarwal, Hodgson, and Somaini (2020) highlight, it is still unclear how assignment mechanisms perform when evaluated regarding educational outcomes. Our focus on graduation rates also gains relevance because students do not necessarily choose schools based on their match quality (Abdulkadiroglu et al., 2020) which could create mismatch and affect graduation.

Second, we also contribute to the literature on using achievement tests and grades in education policy. The informational content of grades gains relevance 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, Egger, and von Ehrlich (2013) implement an RDD and find that the effect of regional transfers in the European Union depends on regions having enough absorptive capacity 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 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 6 and SUB 7 in Table 1, 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

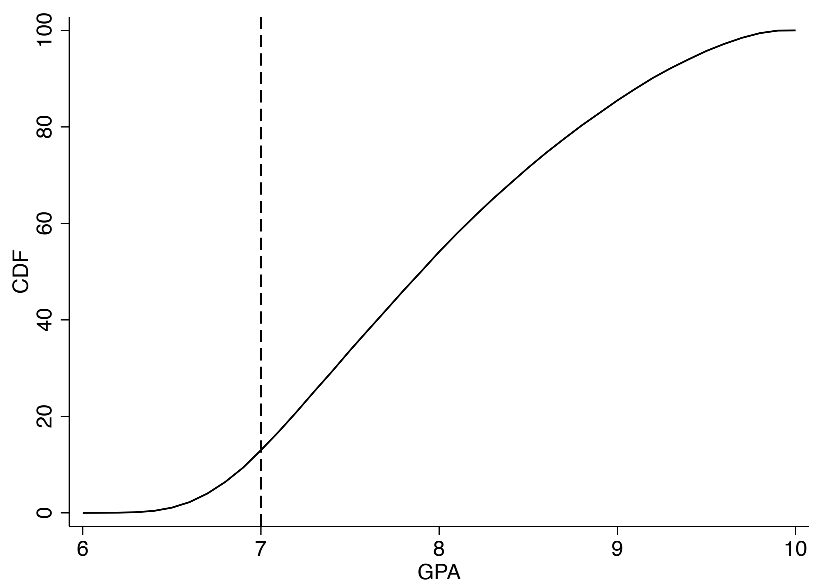
	Number of Schools	Seats	First in ROL	Admission Cut-Off
SUB 1	40	16.9%	6.1%	49.2
SUB 2	179	18.4%	5.8%	35.8
SUB 3	2	0.9%	0.5%	60.5
SUB 4	5	0.3%	0.2%	32.4
SUB 5	186	17.6%	7.7%	44.5
SUB 6	16	8.7%	14.5%	79.6
SUB 7	14	14.1%	48.5%	86.3
SUB 8	215	22.8%	16.1%	47.0
SUB 9	1	0.4%	0.7%	74.0
Total	658	100.0%	100.0%	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 2006 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.

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 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 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). Since all schools use the same priorities, the algorithm is equivalent to the Serial Dictatorship (SD). 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 algorithm in Appendix B.

After implementing the matching algorithm, a student can be matched or unmatched. 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. Unassigned students get the chance to register into schools that still have available seats after the matching process is over.

3 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 296,778 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.

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 mechanism and fully replicate the assignments we observe in the data (Table 2). Being able to replicate the student-school matches observed in the data gives us confidence in the transparency of the admission system.

Table 2: 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

To measure graduation, we collected administrative graduation records during 2010-2012 (3-5 years after admission). 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 subsystems (including all elite schools). For the missing subsystem, we proxy for graduation using participation in a standardized exam that students take at the end of high school. To be consistent in our definition of graduation, we use exam participation in any year between 2010-2012. All the schools belonging to the missing subsystem participated in the standardized exam. We employ students' national identification numbers to merge the admissions data with the graduation or exam records.

Our data collection efforts provide us with two significant advantages. First, we observe application and graduation records for a large number of students, which allows us to study heterogeneity in a RDD (Section 4). Second, having information on GPA allows us to explore a counterfactual admission policy that considers the skills measured by GPA when designing admission priorities (Section 5).

4 RDD

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 enrolment because enrolment at elite schools is almost universal.

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 assigned by the matching algorithm. Some unassigned students participate in a second-round where they choose from schools with empty seats, but elite schools never have empty seats at the end of the matching algorithm.

For the estimation, we follow Kirkeboen, Leuven, and Mogstad (2016) strategy to estimate the effect of attending a particular institution. The main difference is that in our case, we consider only two institutions, elite and non-elite. Equation 1 shows our empirical specification.

$$Y_i = \alpha_0 + \alpha_1 \mathbb{1}[S_i \geqslant c(i)] + \alpha_2 [S_i - c(i)] + \alpha_3 \mathbb{1}[S_i \geqslant c(i)] \times [S_i - c(i)] + \epsilon_i \tag{1}$$

$$c(i) = c_k \text{ for } k \in \{1, ..., 30\} \tag{2}$$

In Equation 1, Y_i is a dummy variable that denotes graduation, S_i is the score in the admission exam. We define $c(i)$ as a function that maps each student with her relevant cut-off, the one that determines whether she gains admission to an elite school or a non-elite school. Equation 2 shows that this cut-off can take 30 different values because there are 30 elite schools. In terms of the empirical strategy in Kirkeboen, Leuven, and Mogstad (2016), we are considering students whose first best is an elite school and their second-best a non-elite school (in the local institution ranking).

We use a local linear regression with a triangular kernel and follow Calonico, Cattaneo, and Titiunik (2014) to obtain the optimal bandwidth. 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. A potential threat to our design is that students could sort themselves to be above an elite school admission cut-off. This is unlikely in our context for two reasons. First, admission cut-offs are determined in equilibrium, after students submit their applications. Second, students submit their applications before they know their score in the admission exam. Our findings are consistent with this, Figure 2 shows the density of the running variable and the confidence intervals for testing continuity. We do not reject continuity of the density at the admission cut-offs (T=-1.2).

In addition, Table 3 shows that other predetermined covariates do not vary discontinuously at the cut-offs.

Figure 2: Continuity test

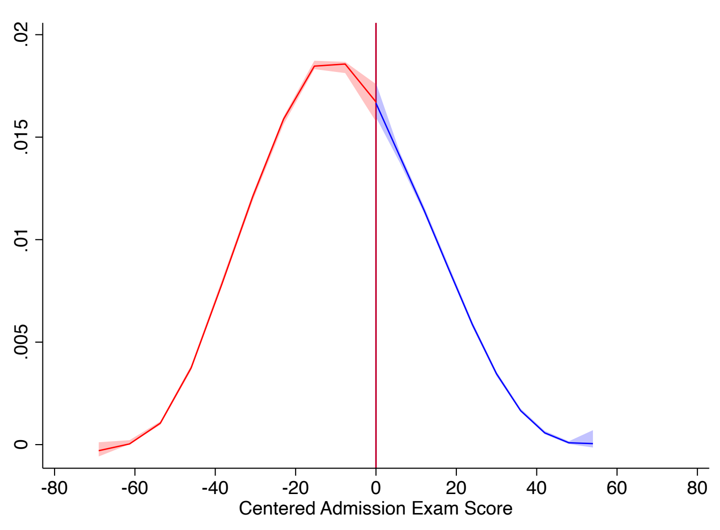


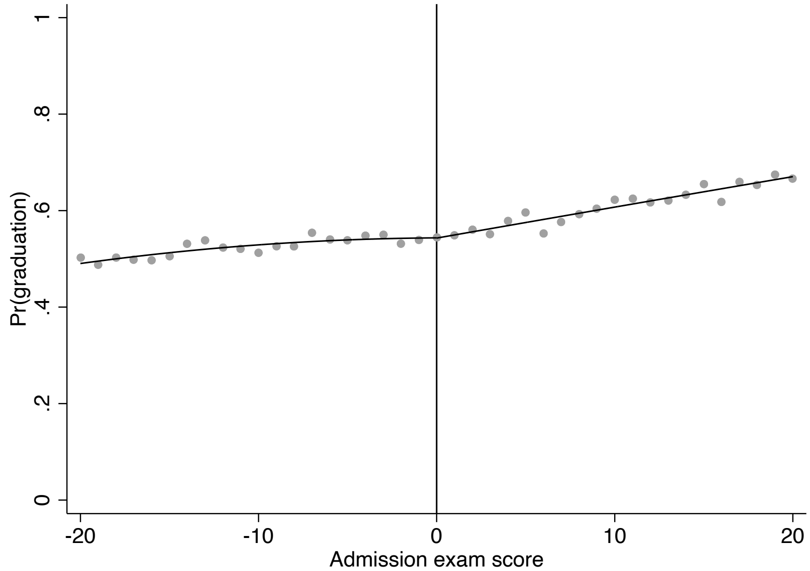
Table 3: Predetermined covariates

	(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

Figure 3 shows a graphical representation of our result without considering heterogeneity. Elite schools do not have an effect on the probability of graduation for students marginally admitted to them. We show the estimated parameter $\hat{\alpha}_1$ and its standard error in Appendix C. The parameter is close to zero and is not statistically significant.

Figure 3: Elite schools effect on graduation



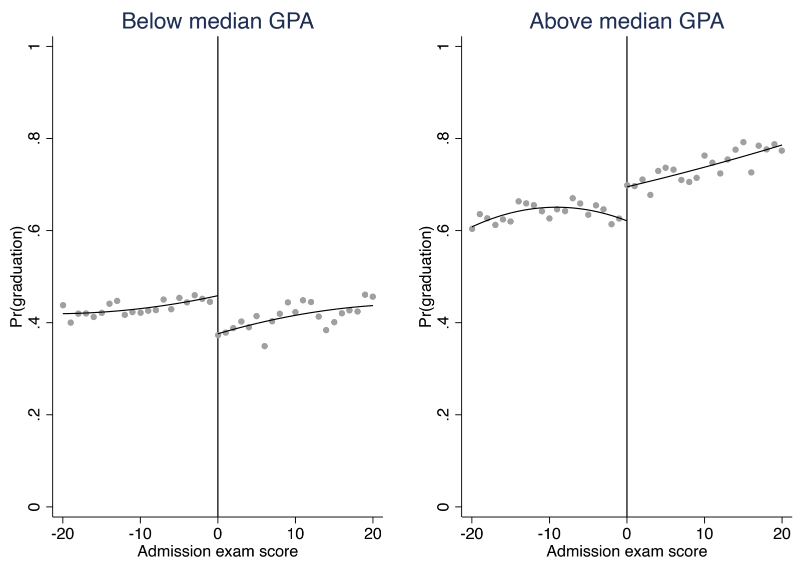
4.2 Heterogeneity by GPA

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 GPA.

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 4 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 C. When we group high and low GPA students, the two effects cancel out and we get the results in Figure 3. 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 4: Elite school admission and graduation by GPA



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 they have lower skills. Instead, that there are gender differences in performance under competitive pressure. In this context, 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.

Consistent with previous research, our data shows that males score higher in the admission exam score, while females have higher GPAs (Figure 5). In the last section, we show 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 next explore the heterogeneity of results by gender.

Figure 5: Admission exam score and GPA by gender

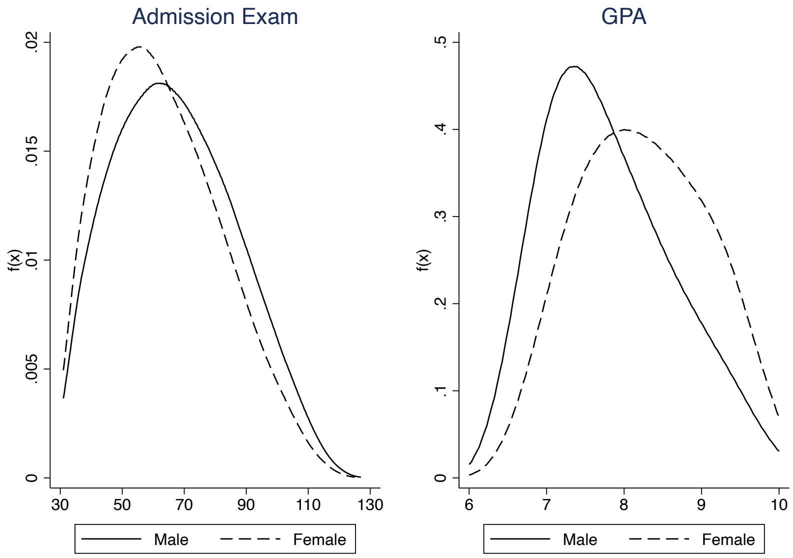
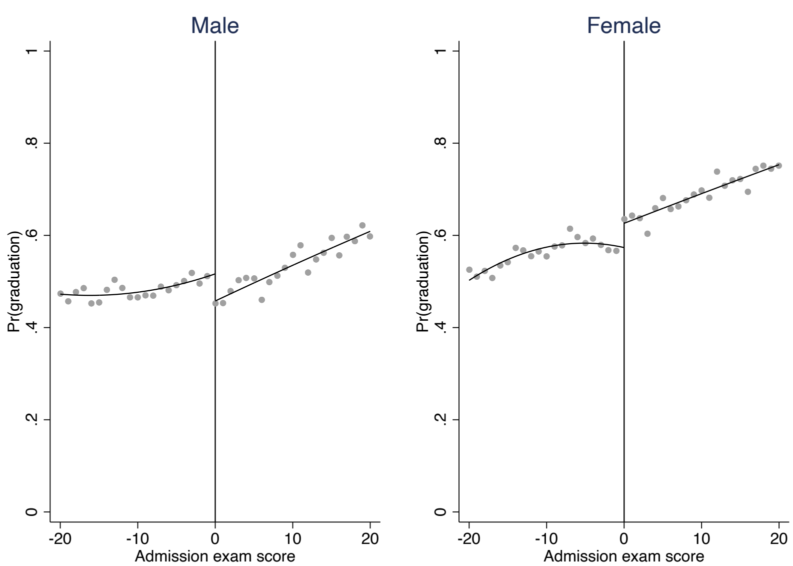


Figure 5 shows the results of implementing an RDD separately for males and females. The effect for males is almost identical (decrease of 6 percentage points) to the effect for students with below-median GPA, while the effect for females almost replicates (an increase of 6 percentage points) the effect for students with above-median GPA. We include point estimates and standard errors in Appendix C. Our results can be explained by differences in the skills that GPA measures between males and females.

Figure 6: Elite school admission and graduation by gender



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 have the skills needed to benefit from them (in terms of higher graduation probabilities).

5 Counterfactual admission policy

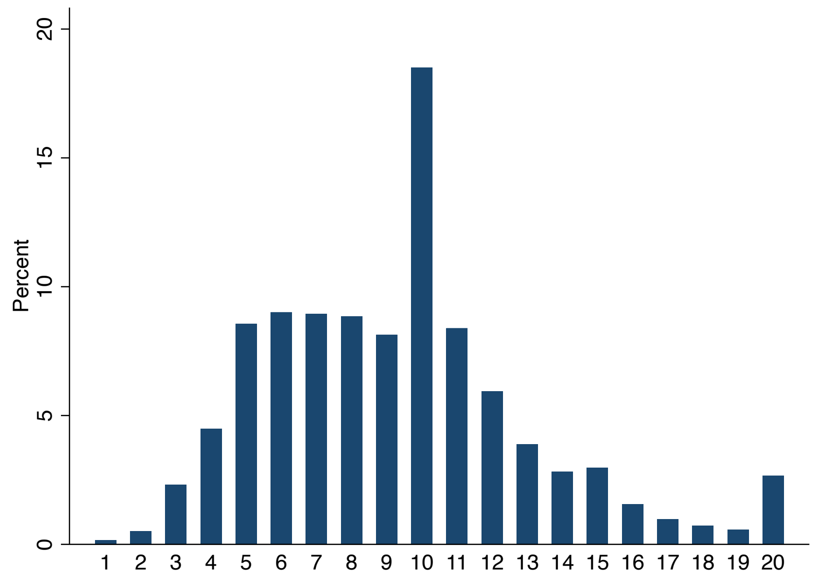
Motivated by our RDD results, we examine the effects of a counterfactual admission policy where elite schools put equal weight on the admission exam score and GPA when defining their priority index. Non-elite schools do not change their priority index and remain using the admission exam score. In terms of the matching algorithm, in the counterfactual, elite schools have a priority index different from that of non-elite schools. This change is equivalent to letting the centralized system use a more general SPDA algorithm that allows for 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 is when students are strategic when choosing their ROLs. The change in priorities would change students' admission probabilities, and strategic students would consider the new admission probabilities when choosing their ROLs. We believe that, in our context, students are not strategic for two reasons.

First, the Serial Dictatorship and SPDA algorithms are 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 7, 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.[2]

[2]Abdulkadirogly, 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

Figure 7: ROLs length in 2007



Second, another case where truth-telling may break even under a strategy-proof algorithm is the strict priority setting. Fack, Grenet, and He (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. The uncertainty in the priority index leads to admission probabilities that are rarely zero ex-ante.

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'

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.

skills at schools are minimal.

To obtain a relationship between students' characteristics and their graduation probability, we estimate index models for high school graduation (Equation 1). We do school-specific estimations to allow flexibility in how individual-level characteristics differentially affect graduation probabilities from different schools. The dependent variable y_{ij} is a binary variable that equals one if student i graduated from high school j, and zero if not. The independent variables (vector x_i) are the score in the admission exam, middle school GPA, gender, and a constant. Notice that the constants capture school-specific effects on the graduation probability. Thus, our graduation model is given by:

$$P_j(x) = P_j[Y = 1 \mid X = x] = E_j[Y \mid X = x] \text{ , where } j \in \{1, ..., 658\} \tag{3}$$

$$P_j(x) = G(\alpha_j + x'\beta_j). \tag{4}$$

Equation (4) provides a mapping between student characteristics and the probability of graduation from school j. The mapping is defined by the parameters α_j, β_j 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. These set of additional controls are motivated by Dale and Krueger (2014) empirical specification. 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.[3] This is the specification we use to predict graduation outcomes in the counterfactual.

Our counterfactual assigns some students to different schools than their initial assignment. For example, consider a student assigned to school j in the data who is assigned to school j' in the counterfactual. To calculate her graduation probability at the new school, we use the mapping from student characteristics to the graduation

[3] 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

probability we previously obtained for school j'. The counterfactual probability of graduation for this student follows Equation 5.

$$\hat{P}_{j'}(x) = G(\hat{\alpha}_{j'} + x'\hat{\beta}_{j'}) \tag{5}$$

We repeat the previous step for all the students that switch schools from the data to the counterfactual. For the students that remain at their initial school in the counterfactual, we use their predicted graduation probability following Equation 4.

Notice that an implicit assumption for this exercise is that the parameters α_j and β_j do not change in the counterfactual. Consider the case where these parameters capture fixed school characteristics such as infrastructure or quality of teachers. Then, the counterfactual is changing the composition of students that interact with these attributes. A more complex case is when α_j and β_j also capture the effect of the average peer quality on a student graduation probability. Even under this case, our counterfactual remains informative if the average peer quality at schools does not change much. Since our counterfactual still adds weight to the admission exam score, the changes in average peer quality (measured by average score and average GPA) are small.

5.1 Results

Our counterfactual exercises result in different allocations of students across schools. In Table 4, 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.

Table 4: Initial 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%	

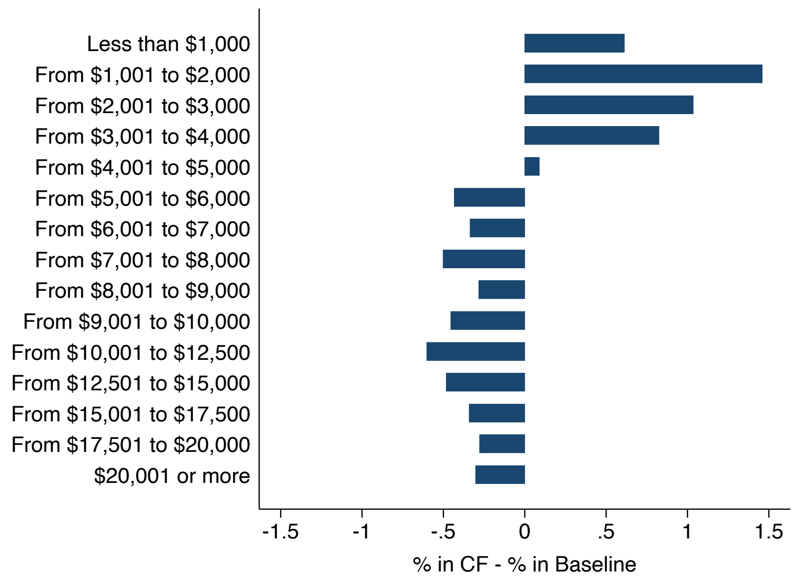
We next investigate if our counterfactual has some consequences in the gender composition of students assigned to elite schools. Table 5 shows that our policy increases the share of female students assigned to elite schools by nine percentage points. This change occurs because females demand elite schools, 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 5 also shows that our counterfactual increases elite schools' graduation rate by eight percentage points. The graduation rate increases because the counterfactual assigns more high GPA students to elite schools, and these students have the skills needed to graduate from them.

Table 5: Changes in composition and graduation rates

	Initial	Counterfactual	Diff
Elite			
Female	45.12%	54.33%	9.22
Graduation	64.58%	72.31%	7.73
Non-Elite			
Female	52.91%	50.00%	-2.91
Graduation	45.88%	44.70%	-1.18

In addition, in Figure 8, 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 8: Changes in income composition of students at elite schools



5.2 Welfare

To approximate effects on 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 6, we show that there are no changes in the position in their ROLs students are assigned on average. 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 6: 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 our results in Table 6 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' 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 welfare in miles.

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

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

$$U_{ij} = \underbrace{\delta_j + x_j'\Gamma z_i - D_{ij}}_{V_{ij}} + \epsilon_{ij} \tag{7}$$

In Equation 6, 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. We group individual invariant regressors in coefficients δ_j that capture school fixed-effects. In vector z_i, we include individual-level characteristics: a standardized exam score (different from the admission exam), GPA, and gender. We do not include the admission exam score because students do not have this information when choosing their ROLs. 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.

We follow Beggs, Cardell, and Hausman (1981) and estimate preferences using a Rank-Ordered Logit. The probability that student i chooses her ROL is:

$$P[ROL_i = (j_1, j_2, ..., j_{K_i}) \mid x_j, z_i, D_{ij}; \theta] = \frac{exp(V_{ij_1})}{\sum_{l \in J} exp(V_{il})} \times ... \times \frac{exp(V_{ij_K})}{\sum_{l \in J \setminus \{j_1, ..., j_{K_i - 1}\}} exp(V_{il})}. \quad (8)$$

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

$$L(\theta) = \sum_{i}^{N} logP[ROL_i = (j_1, j_2, ..., j_{K_i}) \mid x_j, z_i, D_{ij}; \theta]. \quad (9)$$

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 obtained from her assignment in the data and her assignment in the counterfactual. Notice that the observed ROLs impose restrictions in the space where ϵ_{ij} can be. We calculate student welfare in the data as:

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

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

$$W(\mu_{CF}(i)) = E\left[U_{i\mu_{CF}(i)} \mid V_{ij}, ROL_i\right]. \quad (11)$$

Consistent with our results in Table 6, welfare distribution does not change much in the counterfactual (Figure 9). But as we also know from Table 6, there is heterogeneity in this effect. Figure 10 shows that the welfare distribution is shifted to the right for females while shifted to the left for males. Average female welfare increases 0.5 miles, and average male welfare decreases 0.4 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 9: Change in welfare

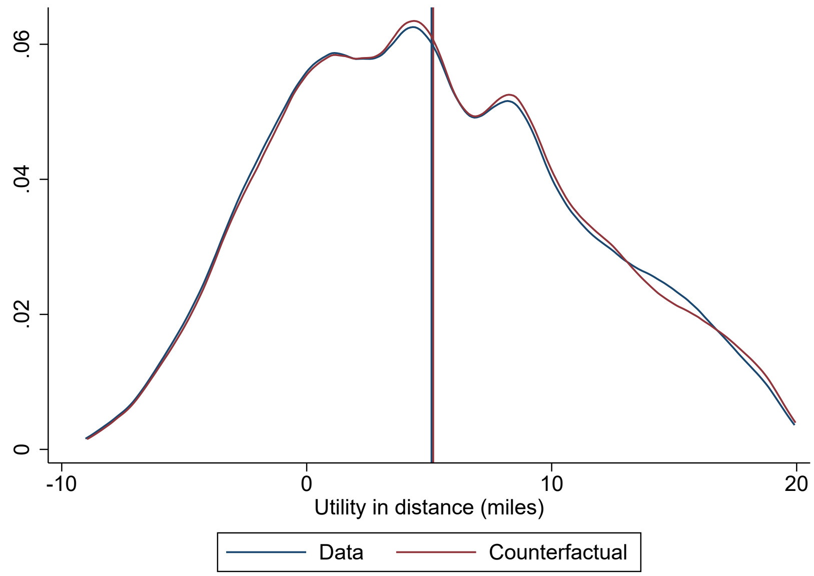
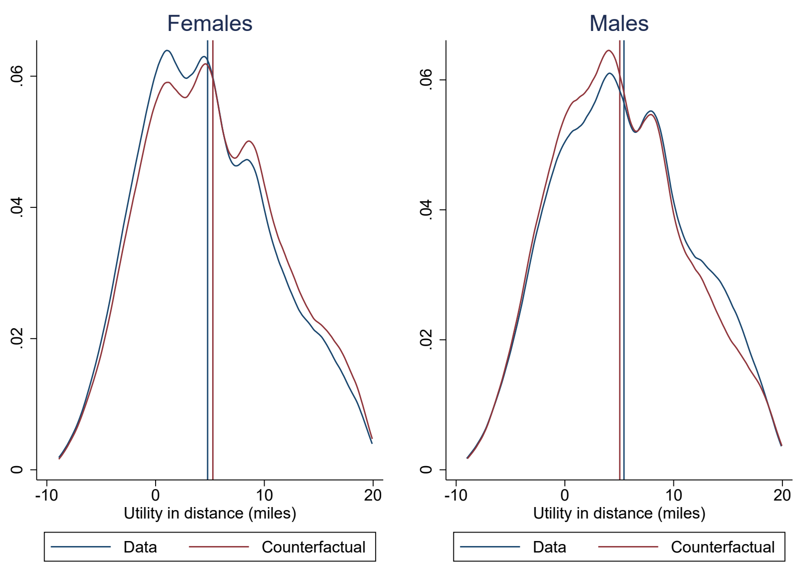
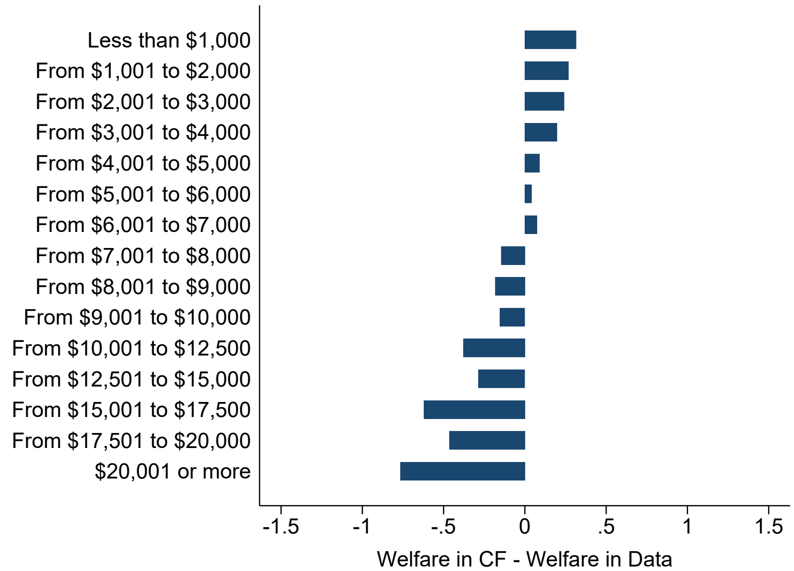


Figure 10: Change in welfare by gender



Lastly, as we show in Figure 8, 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 11, 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, 79% of students come from households with family incomes of less than or equal 7,000 pesos.

Figure 11: Change in welfare by income



6 Conclusions

In this paper we show that the choice of a priority structure 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, because some priority structures could match students without the necessary skills to graduate with the most academically demanding schools. School priorities play an important role when evaluations of centralized education systems go beyond efficiency measures based on revealed preferences and also 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 elite schools including middle school GPA as part of their priority index. We focus on GPA because previous literature shows that grades measure non-cognitive skills to a higher extent than achievement tests, and that non-cognitive skills influence 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, as they have higher GPAs than males. Our first set of results motivate the importance of taking into account heterogeneity in skills when studying how elite schools affect the graduation probability for students at the margin of admission.

Guided by our first set of results, we then estimate a graduation model for each school and a model of school choice to study the effects of a counterfactual admission policy where elite schools put equal weight on GPA and the admission exam score to prioritize students. 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. Third, the average welfare in the system remains the same, but females' and low-income students welfare increases while males and high-income students welfare decreases.

A limitation of our paper is that our counterfactual could induce additional behavioural responses that we are not currently studying. For example, it could change students' effort allocation between exam preparation and middle school coursework. Also, it could increase the number of high middle school GPA students that choose to participate in the centralized system (extensive margin) that were previously discouraged by the lack of weight on GPA. Lastly, it could create incentives for middle school grade inflation making prior GPA a less informative measurement of skills. These considerations are left for future research.

From a policy perspective, our results indicate that adding some weight to middle school GPA when defining admission priorities to elite over-subscribed schools can be beneficial for the centralized system in Mexico City. More broadly, other centralized systems similar to the one studied here in their reliance on a unique standardized test to define school priorities could also benefit from adding some weight to the skills measured by grades. Examples of such a systems are the centralized education systems in Romania, Kenya, and the college admission system in China.

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A The admission exam

Table 7: 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 7 shows the different sections of the admission exam. The total score is simply 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 mechanism

The central planner define priorities that all schools follow to rank students 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.

C Estimates

Table 8: Graduation

	(1) All	(2) Low GPA	(3) High GPA	(4) Males	(5) 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

D SPDA mechanism

For the SPDA mechanism, each school defines its own priorities over the students and each student defines her ROL. The matching algorithm is as follows [4]:

- 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 highest priority, and rejects all others.
- 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 they 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 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.

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