Quantifying the Perceived Value of Elite Schooling

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Abstract

Evaluation of education policy often hinges on quantifying the value of better schooling. When school assignment is centralized and merit-based, students devote much of their effort to improving admission test performance, as test scores largely determine access to desirable schools. This study focuses on student effort and family resources devoted to elite school admission exam preparation as an approach to the value students and their families place on school quality. I exploit a policy rule that sets a middle school GPA threshold for students' eligibility for elite high school admission in the Mexico City Metropolitan Area, and analyze the difference in test scores and the probability of attending private admission exam preparatory courses at the policy threshold using regression discontinuity estimates. I find that students who are eligible for elite schools, compared with those who are not, are 34% more likely to retake the high school admission exam, score 0.10 standard deviations higher, and are 15 percentage points more likely to take private preparatory courses.

Keywords: effort, selection, investment, regression discontinuity, test scores.

JEL classification: I21, I25, I28.

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1 Introduction

The design of effective education policies depends on one's ability to assess the value families place on school quality. Families often go to great lengths to enroll their children in what they consider to be better schools. These efforts include moving to a different school district (Black, 1999; Holme, 2002), leveraging family and friends networks (Cox et al., 2021), paying for private tutoring (Kim and Lee, 2010; Sriprakash et al., 2016), queuing in person before registration opens (Fong and Faude, 2018), investing in test preparation (Dang and Rogers, 2008), retaking the admission exam (Bound et al., 2009), and even bribing corrupt officials (Meier, 2004; Chow and Thi, 2013; Borcan et al., 2017). Yet, despite such behavioral evidence of revealed preference, it is yet to be applied, to my knowledge, to obtain causal estimation of the value families place on better schooling.

In centralized school admission systems, students efforts primarily devoted to activities that improve entrance exam performance, since test scores serve as the primary, and often the sole criterion for admission to a desirable school.[1,2] Exploiting a GPA policy rule that disqualifies some students from elite schools within the public high school admission system of the Metropolitan Area of Mexico City, I perform regression discontinuity (RD) design estimation to quantify the value families place on the prospect of gaining admission to elite schools. The extra effort aimed at it is gauged by comparing the test scores of students just above and below the eligibility threshold. I also provide evidence of student self-selection in retaking the admission exam and enrollment in private preparatory courses due to the prospect of attending elite schools. Although exam retaking, intense exam preparation effort, and financial investment in it are extensively documented in the education literature, causal estimates quantifying the pursuit of superior educational opportunities remain elusive, as these behaviors are endogenous to unobserved factors such as ability and motivation.

I identify the extra exam preparation effort at the elite school eligibility threshold subject to four institutional characteristics of the high school admission process of the Mexico City Metropolitan Area. First, the seat allocation mechanism is implemented through a serial

[1]Some countries that use centralized matching mechanism in *high school* include: China (Wang and Zhou, 2020), France (Hiller and Tercieux, 2014), Ghana (Ajayi, 2024), Mexico (Dustan et al., 2017), Romania (Pop-Eleches and Urquiola, 2013), Singapore (Teo et al., 2001), Turkey (Akyol and Krishna, 2017), and the United States (Abdulkadiroğlu et al., 2014). For *university* admissions, examples include: Australia (Artemov et al., 2017), Brazil (Machado and Szerman, 2016), Chile (Rios et al., 2021), China (Chen and Kesten, 2017), Hungary (Biró, 2007), Norway (Kirkeboen et al., 2016), Spain (Luflade, 2018), and Turkey (Karadal et al., 2013)

[2]Admission systems in other countries, that do not rely on centralized matching, may also place a heavy weight on standardized exams. For example, in the United States, the SAT and ACT historically played a central role in college admissions, while in South Korea, the College Scholastic Ability Test (CSAT) is the primary determinant of university admission. This paper also speaks to such systems.

dictatorship algorithm that constructs priority indexes solely based on student entrance exam test scores. This ensures that students can only improve their chances of admission to a more preferred school by improving their test performance. Second, according to an administrative rule, students with middle school GPAs below 7.0 (out of 10) are ineligible to access elite high schools. This effectively divides applicants into two distinct groups: those eligible for admission to elite schools and those barred from such opportunities. Third, the elite segment of the market is clearly defined; it consists of high schools affiliated with the most public prestigious universities in the country, namely the Universidad Nacional Autónoma de México (UNAM) and the Instituto Politécnico Nacional (IPN). Finally, transfers between high schools are not allowed; hence, retaking the admission exam for *de novo* admission is the only available option to gain access to a different school.

The analysis focuses on admission exam retakers, since students taking the high school entrance exam for the first time are yet to finish middle school and to learn their final middle school GPA. This uncertainty implies, in particular, that relatively weak students who face uncertainty whether their GPA will meet the 7.0 minimum eligibility requirement for admission to elite high schools will not find this out until after their first time testing. This genuine uncertainty is indeed evidenced by the fact that first-time test takers with (*ex post* revealed) GPA near the 7.0 policy threshold apply in similar proportions to elite and non-elite schools, leading, also, to comparable levels of exam preparation. Consequently, no significant differences in test scores are expected near the threshold for students taking the admission exam for the first time. In contrast, by the time students decide to retake the admission exam, they know their middle school GPA and, therefore, face no uncertainty about their elite school admission eligibility status. As a result, all students with GPA below 7.0 who happen to retake the exam exclude elite schools from their application portfolio, whereas students with GPA at or above 7.0 include them in comparable proportions as in the first admission process. Accordingly, for retakers the resolution of uncertainty renders eligibility salient and induces differential elite-school listing, which in turn produces a discontinuous increase in exam-preparation effort, and thus an anticipated difference in test scores, at the 7.0 threshold. Using the subpopulation of retakers, however, poses a significant identification threat, as the students self-select to retake the entrance exam, which has a potential to violate the smoothness assumption of the RD design. I estimate that the presence of the 7.0 GPA eligibility threshold is responsible for 3.4 percentage point higher share of retakers in student population, than it would have been without this eligibility constraint. Based on a baseline retake rate of 10% at the policy threshold, this figure represents an increase of 34%.

I mitigate the concern about selection by implementing econometric approaches that vary in their underlying assumptions (e.g., smoothness and unconfoundedness) and target estimands within the RD design framework. As a baseline, I estimate the canonical regression discontinuity (RD) design as in Hahn et al. (2001), which does not address selection. To restore smoothness, I use the first difference in the outcome variable (Lee and Lemieux, 2010). [3] To quantify whether the effects are significant, I employ sharp bounds on the LATE point estimates (Dong, 2019). To complement the analysis, I relax the continuity assumptions in the RD design and impose the assumption of unconfoundedness, which allows the estimation of conditional average treatment effects (CATE). Under unconfoundedness, I estimate two additional models: one that controls for observable characteristics using a linear random forest (Athey et al., 2019), and another that accounts for unobservable characteristics, proxied by the share of elite schools in each student's submitted application list (Dale and Krueger, 2014).

The results consistently indicate that students' elite school eligibility leads to higher performance on retake entrance exam on the eligibility margin. That is, students marginally above the 7.0 GPA threshold score higher than otherwise comparable students marginally below it. Estimates from the canonical RD design specification show a 0.23 standard deviation (sd) increase in test scores. Based on the first difference and controlling for observable models, I find an impact of 0.10 sd, while controlling for unobservables characteristics, through student application choices, yields the estimate of the effect of 0.18 sd. Sharp bounds range from close to zero to 0.37 sd. The preferred model estimate is 0.10 sd and emerges from the first-difference specification, which restores smoothness. Replicating the serial dictatorship algorithm one hundred times, and each time simulating a 0.10 sd decrease in the observed test scores of retakers eligible for elite schools, which corresponds to the additional effort exerted in pursuit of elite school admission, I find that the probability of admission drops by 5 percentage points (pp) from a baseline elite admission rate of 28.4% for this subpopulation.

Although comparing estimates across studies in education literature is notoriously hard, I benchmark my estimates against previous work analyzing achievement increases in the same admission test. Cabrera-Hernández et al. (2023) estimate that adding 3.5 hours of daily instruction in elementary school increases scores by 0.05 sd; Fabregas (2023) report a 0.03 sd increase from having middle school classmates whose prior achievement is on average 0.4 sd above the mean in the middle school entry exam; and Padilla-Romo and Peluffo (2023) find a 0.02 sd decrease from adding one peer exposed to local violence to a class of 20 students.[4]

[3]By taking the difference in outcomes across the two periods and applying the RD estimator, I am effectively estimating a difference-in-discontinuities parameter. However, since the analysis only compares two periods, there is no scope to recover or test for differential trends. For this reason, I do not adopt the difference-in-discontinuities terminology

[4]To the best of my knowledge, these are the only studies that analyze achievement in the same test.

The preferred model point estimate from my findings is twice as large as those reported in the aforementioned studies. This suggests that students and their families assign a significantly high value to admission into elite schools.

The results further indicate that families whose children are eligible to attend elite schools allocate greater financial resources to pay for preparatory courses to retake the entrance exam. Eligibility increases enrollment in private preparatory courses by 15 percentage points (pp). In contrast, ineligible students are about 14 pp more likely than their elite-school eligible counterparts to participate in preparatory courses offered directly at their middle schools, which are free of charge and thus provide a costless alternative to the paid private options. The cost of preparatory high school admission courses range from 6.5% of average monthly household income in a wealthy borough to up to 60.2% in a disadvantageous one. These figures are consistent with the notion that student families attach high value to the opportunity to pursue admission to elite high schools, hence their considerable financial commitment.

The main contribution of this paper is to the literature evaluating the perceived quality of educational institutions. Generally this literature follows two main paths. One focuses on post-schooling outcomes, including performance on exit examinations (Pop-Eleches and Urquiola, 2013; Abdulkadiroğlu et al., 2014; Estrada and Gignoux, 2017; Fabregas, 2023) and labor-market earnings (Hoekstra, 2009; Zimmerman, 2019; Chetty et al., 2023). The other seeks to quantify what families value when choosing schools, through measures of willingness to pay (Black, 1999), willingness to travel (Ainsworth et al., 2023; Ngo and Dustan, 2024), and peer quality (Rothstein, 2006; Allende, 2019). Building on this last strand of literature, this study contributes by quantifying the revealed value students and their families place on better schools, as reflected in the additional effort devoted to exam preparation.

A second contribution is to the literature on *shadow education*, understood as private supplementary tutoring and other paid learning activities that take place outside regular school hours. Previous work analyzing the determinants of *shadow education* has found that income (Dang and Rogers, 2008), peer effects (Pan et al., 2022; Dai and Zhou, 2025), and the pursuit of additional human capital (Bray, 1999) are associated with the demand for schooling outside the regular classroom. This paper adds by establishing a casual link between the pursue of elite educational opportunities and family investment in preparatory courses.

Related work in the context of high school admission in the Mexico City Metropolitan Area examines family networks and school choice. Dustan (2018); the risk of dropping out of elite schools Dustan et al. (2017); preferences, access, and the STEM gender gap Ngo and Dustan (2024); and school stratification Estrada (2017), among other topics.

A third contribution pertains to the emerging literature on high stake exam retaking. Previous studies find that retakers crowd out admission chances for first-time takers arguably reducing overall welfare (Krishna et al., 2018), and that retaking increases both the probability of enrolling in a four-year college and future earnings (Goodman et al., 2020). While existing evidence suggests that the pursuit of better schooling is one of the main reasons for retaking (Ono, 2007; Bizopoulou et al., 2024), causal estimates of the magnitude of this behavior are not yet readily available. The most closely related causal evidence comes from studies showing that male students are more likely to retake highly competitive admission exams than their female counterparts (Landaud and Maurin, 2020; Kang et al., 2024). This paper is the first to my knowledge to provide a causal estimate of the proportion of students, in a well-defined relevant subpopulation, who retake entrance exams with the objective of gaining admission to superior quality (elite) educational institutions.

The paper is organized as follows. Section 2 provides a description of the institutional context and presents the data. Section 3 introduces the empirical strategy. Section 4 presents the estimation results. Section 5 explores the validity of the RD design. Section 6 examines the impact of the GPA policy on families' financial investment in student preparation for exam retaking. Section 7 concludes.

2 Institutional Context

In the transition from middle school to high school, students in the Mexico City Metropolitan Area who desire to continue their studies in a public high school are required to take a placement exam designed by the Commission of Public Institutions of Upper Secondary Education (COMIPEMS), commonly known as COMIPEMS exam. The COMIPEMS is composed of nine high schools systems that have around 600 schools and school-programs in total.[5,6] Of the nine systems, the UNAM- and IPN-affiliated high schools are considered elite.[7]

[5]Excluding UNAM and IPN the school systems are: Colegio de Bachilleres (COLBACH), Colegio Nacional de Educación Profesional Técnica (CONALEP), Dirección General del Bachillerato (DGB), Dirección General de Educación Tecnológica Industrial y de Servicios (DGETI), Dirección General de Educación Tecnológica Agropecuaria y Ciencias del Mar (DGETAyCM), Secretaría de Educación del Gobierno del Estado de México (SE), and Universidad Autónoma del Estado de México (UAEM).

[6]A school-program refers to a specific separately administered area of specialization that may exist within an educational institution (high schoo). Not all high schools run such programs. For instance, IPN and UNAM do not provide separate programs within their schools. In contrast, the CONALEP and SE systems offer a diverse array of programs spanning disciplines such as administration, mechanics, and electricity.

[7]Elite schools, defined as those affiliated with the IPN and UNAM systems, have been widely used in the literature. Some studies that use this definition include Ortega Hesles (2015), Dustan et al. (2017), Estrada and Gignoux (2017), Estrada (2017), Pariguana and Ortega (2022), Bobba et al. (2023), and Ngo

UNAM and IPN high schools are distinguished by their superior faculty and infrastructure. These institutions boast state-of-the-art classrooms and laboratories that enhance students' learning experience. Additionally, facilities such as modern gymnasiums and sports courts offer enriching extracurricular activities. The staff have credentials that exceed other educational systems. Table Table 1 shows the proportion of teachers holding bachelor's, master's and PhD's degrees by high school type (general or technological) and school system.[8] Within general high schools, UNAM has a higher share of teachers with a Master's degree (22%) and a PhD (3%) compared to other general high schools. Similarly, within technological high schools, IPN stands out, with 88% of its teachers holding higher education degrees, compared to lower shares in other systems: 73% in DGETA, 72% in DGETI, and 82% in SE.

Beyond infrastructure and faculty, affiliated UNAM and IPN high schools serve as important gateways to their respective universities. UNAM grants its high school graduates admission through *pase reglamentado*, which guarantees UNAM university access without entrance exam.[9] For the 2015-16 academic year, all 26,611 UNAM affiliated high school graduates who applied to UNAM were accepted. In contrast, among the 217,663 applicants who were required to take UNAM's university entrance exam, only 11% gained admission (UNAM, 2023). Empirical evidence indicates that families regard enrollment in UNAM affiliated high schools as a strategic pathway to obtain admission to UNAM university (Chen and Pereyra, 2019). The IPN does not grant preferential university admission to its high school graduates. However, IPN affiliated high schools provide preparatory courses to improve student performance on their university admission exam, thus facilitating access despite the lack of a formal priority status. In the academic year 2021-22, approximately 60% of graduates of IPN affiliated high schools were admitted to IPN, compared to only 20% of applicants outside its high school system (IPN, 2022; Instituto Kepler, 2023).

The COMIPEMS exam test score constitutes the only criterion to determine students' priority in seat allocation for high school public seats in Mexico City metro area. School as-

and Dustan (2024).

[8] In the Mexico City Metropolitan Area, high schools are categorized into three distinct types: general, technological, and vocational. General high schools are designed to equip students for higher education. Technological high schools provide students with both a technical degree and the necessary preparation to pursue further education, and vocational high schools focus on preparing students for a technical degree.

[9] *Pase reglamentado* is a policy that provides admission into UNAM without requiring an entrance examination, contingent upon their performance on high school education. Priority is given to candidates who have completed high school in three years and have achieved a minimum GPA of nine out of ten. Subsequent seats are allocated to students who have a GPA greater than seven and have completed their high school education within a span of four years, subject to availability. In the 2015–16 academic year, 53% of UNAM's university seats were filled by students admitted through the *pase reglamentado* mechanism.

Table 1: Educational Qualifications of Teachers across School Systems (2015)

System	Bachelor (%)	Master (%)	PhD (%)	Rest (%)	Total teachers
General High School					
COLBACH	91.7	1.2	0.1	7.0	2,925
DGB	78.6	5.3	2.1	14.0	169
UNAM	72.8	21.9	3.2	2.1	6,365
SE[1]	73.6	10.7	0.3	15.4	3,743
UAEM	77.8	6.9	0.2	15.1	804
Technological					
DGETA	59.7	8.3	5.1	26.9	63
DGETI	64.8	7.1	0.4	27.7	2,188
IPN	82.9	4.7	0.3	12.1	3,242
SE[2]	70.9	10.8	0.4	17.9	1,491

Notes: The table shows the share of teachers by educational attainment, based on data from Survey 911 conducted by the Mexican Ministry of Education.
[1] Includes general high schools administered by the State of Mexico's Ministry of Education.
[2] Includes technological high schools administered by the State of Mexico's Ministry of Education.

signments are determined through a serial dictatorship mechanism, in which schools set their capacities, students are ordered from the highest to the lowest score, upon which the applicants are considered sequentially. For each student, the algorithm moves down the students' individual rank order list (ROL), that is, the schools to which a student seeks admission, starting from the student's top choice, verifying if there are remaining seats, and assigning them to their preferred feasible option. Students who exhaust all their listed options without being matched can still enroll in schools with remaining capacity once the algorithm is completed, as a separate subsequent process.[10] This allocation mechanism produces admission cutoffs, defined as the test score of the last admitted student, for each school. By definition, students in their matched school must have tested at or above the school cutoff. In this setting, students could have improved their match only by achieving a higher COMIPEMS exam score. For elite school admission, there is an additional requirement of applicants to have middle school GPA of at least 7.0 out of 10. This additional requirement does not alter how the serial dictatorship algorithm operates; rather, it removes elite schools from the ROL of students with a GPA below 7.0, thereby deeming them inadmissible by construction.

The high school application process begins six months before the COMIPEMS exam. Ninth graders receive a booklet containing relevant information about the admission process, including details about high school programs' characteristics and the information about prior three years' school admission cutoffs. Between February and April, after receiving the

[10] Upon completion of the serial dictatorship algorithm, schools with unfilled seats announce their remaining capacities, from which unmatched students may subsequently select a school.

booklet, participating students complete a registration form containing detailed questions on behavior, sociodemographic characteristics, and other related topics. Students are also required to submit a ROL containing up to 20 high schools, ranked from most to least preferred. The COMIPEMS exam takes place in June, at the end of the school year (See Figure 1 below for a detailed timeline of high school assignment process). The COMIPEMS exam consists of several sections that assess subject-specific knowledge, with a total maximum score of 128 points.[11] This score serves as the priority index in the serial dictatorship assignment algorithm.

Due to the timing of the admission process, at the time of their first-time high school application, students do not have knowledge of their ultimate middle school GPA. As a result, the majority of students who will end up falling below the elite high school eligibility GPA threshold optimistically include these schools in their ROL, in the hope of achieving GPA of at least 7.0.[12] After learning their final GPA, students who fall below the eligibility threshold adjust their subsequent applications by omitting elite schools from their ROL. Table 2 presents the proportions of retakers, in each GPA tier, who included an elite school in their ROL in their first and second applications. In 2015, respectively, 84% and 90% of the retakers, with GPA slightly below the threshold (6.9 GPA) and at the threshold (7.0 GPA), included at least one elite school in their ROL during their first-time application. In their next attempt, these proportions shifted to 1% and 86%, respectively, clearly indicating that students revise their ROLs in response to their realized GPA.

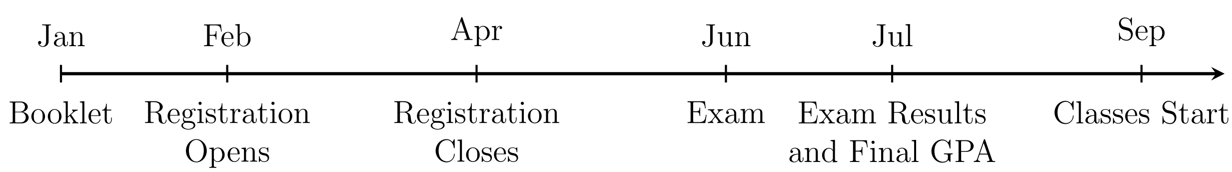


Figure 1: Public High School Admission Timeline

Notes: The figure depicts the main stages of the public high school admission process, beginning with the distribution of the instruction booklet and ending with the start of high school classes.

[11]The COMIPEMS evaluates the following areas: Verbal Skills (16), Spanish (12), History (12), Geography (12), Civic and Ethical Education (12), Mathematical Skills (16), Mathematics (12), Physics (12), Chemistry (12), and Biology (12). The global score is the sum of these components.

[12]See Appendix A1 for supporting evidence.

Table 2: Share of Students Retaking the COMIPEMS Exam Listing at Least One Elite School

	First Attempt (2015)			**Second Attempt (2016)**			
GPA	**First**	**Top 5**	**All**	**First**	**Top 5**	**All**	**N**
6.5	0.58	0.65	0.71	0.01	0.01	0.01	180
6.6	0.58	0.66	0.71	0.01	0.01	0.01	304
6.7	0.65	0.72	0.79	0.01	0.01	0.01	351
6.8	0.63	0.71	0.77	0.00	0.00	0.00	550
6.9	0.70	0.79	0.84	0.01	0.01	0.01	586
7.0	0.79	0.86	0.90	0.75	0.82	0.86	985
7.1	0.80	0.87	0.90	0.77	0.85	0.88	1,023
7.2	0.80	0.87	0.91	0.78	0.83	0.86	1,089
7.3	0.81	0.87	0.90	0.79	0.84	0.87	1,115
7.4	0.82	0.86	0.89	0.80	0.85	0.87	1,053
7.5	0.84	0.88	0.91	0.80	0.85	0.87	1,153
7.6	0.86	0.90	0.92	0.80	0.86	0.88	1,103
7.7	0.87	0.90	0.92	0.83	0.86	0.89	1,052
7.8	0.88	0.91	0.93	0.83	0.88	0.90	1,036
7.9	0.89	0.92	0.93	0.87	0.90	0.92	1,014
8.0	0.90	0.94	0.95	0.87	0.91	0.92	1,066

Note: This table shows the share of students who ranked at least one elite school in their ROL, either as their first choice, within the top five, or anywhere in the list.

Elite school admission is substantially more competitive compared to non-elite ones. The ratio of students ranking UNAM and IPN high schools as their first option to the total number of seats available is 5 and 2.5, respectively, while such ratios for non-elite institutions are relatively low, with the maximum at around 1 (see Figure 2). UNAM and IPN demand-supply ratios indicate that, even after all available seats are filled, there remains a deficit of approximately four applicants per available seat at UNAM and one and a half at IPN. The high levels of competition for elite school admission is reflected in significantly higher admission exam cutoff for such schools (Figure 3). The average test score for elite admission is 1.8 standard deviations higher than that for non-elite schools.

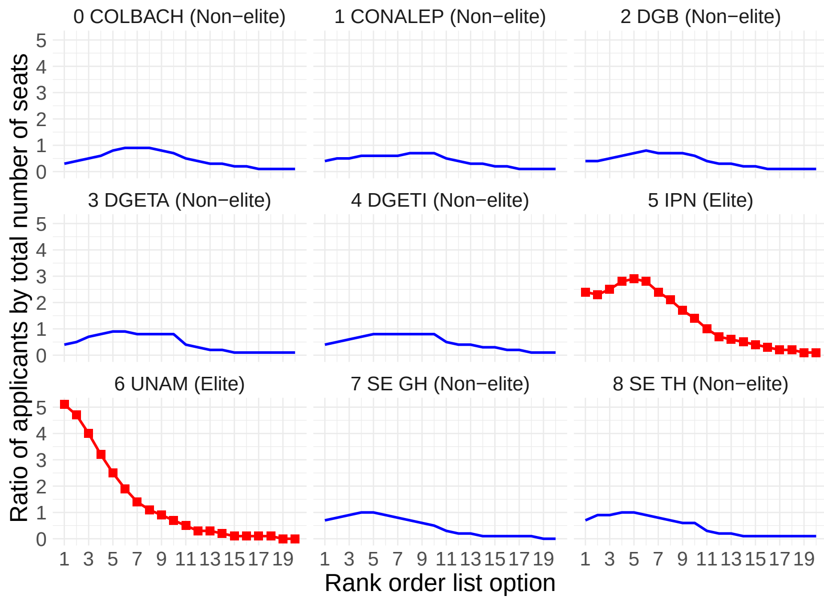


Figure 2: Over-subscription

Notes: This figure shows the ratio of applicants to available seats across school systems by ROL position. The ratio is calculated as the number of students ranking a school as their k-th preferred option divided by the total seat capacity of that school system.

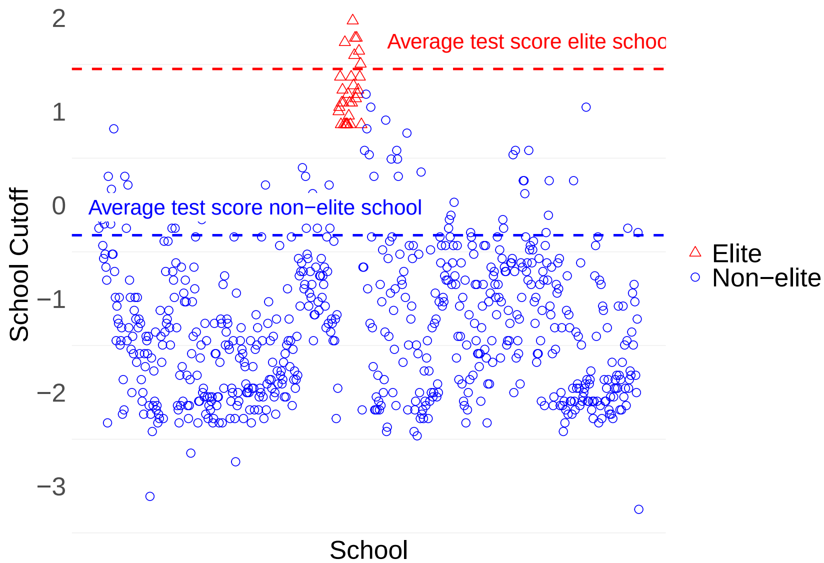


Figure 3: School cutoffs in 2016

Notes: This figure shows the resulting cutoffs after applying the serial dictatorship algorithm. Triangles indicate elite schools, while circles denote non-elite institutions. The test scores are normalized to have a mean of zero and a standard deviation of one.

Given the high-stakes nature of the COMIPEMS exam, private preparatory courses have proliferated as a means of improving students' admission prospects. Combining the data from 2022 survey of the cost of private preparatory COMIPEMS courses conducted by the Federal Consumer Protection Office (PROFECO) with borough-level household income estimates provided by the National Institute of Statistics and Geography (INEGI) for the same year helps assess affordability of the courses Table 3 presents the cost of private preparatory courses for the COMIPEMS exam as a share of average household income across the boroughs of Mexico City. The data reveal considerable variation in the financial burden of these courses across boroughs: while in Benito Juárez the cheapest options represent approximately 6.5% of monthly household income, in Milpa Alta the cost increases to more than 60%. In intermediate cases, such as Tláhuac, Venustiano Carranza, and Xochimilco, families would need to allocate between one-quarter and nearly one-half of their monthly income to pay for these courses.

Table 3: Cost of Private Preparatory Courses for High School Admission and Household Income by Borough

Borough	**Monthly Income** (MXN)	**Cost** (MXN)		**Income share** (%)	
		Lowest	**Highest**	**Lowest**	**Highest**
Álvaro Obregón	31,604	3,600	–	11.4%	–
Azcapotzalco	26,481	3,600	6,945	13.6%	26.2%
Benito Juárez	53,845	3,500	8,400	6.5%	15.6%
Coyoacán	31,768	5,500	10,000	17.3%	31.5%
Cuajimalpa de Morelos	30,484	5,500	6,945	18.0%	22.8%
Cuauhtémoc	34,567	3,750	5,946	10.8%	17.2%
Gustavo A. Madero	25,565	3,200	9,980	12.5%	39.0%
Iztacalco	26,983	5,000	8,360	18.5%	31.0%
Iztapalapa	24,285	4,200	6,000	17.3%	24.7%
Magdalena Contreras	28,842	5,000	11,000	17.3%	38.1%
Miguel Hidalgo	39,982	4,500	5,900	11.3%	14.8%
Milpa Alta	18,116	10,900	–	60.2%	–
Tláhuac	20,408	5,000	12,000	24.5%	58.8%
Tlalpan	30,492	4,000	12,000	13.1%	39.4%
Venustiano Carranza	26,744	5,000	12,000	18.7%	44.9%
Xochimilco	23,305	6,000	9,900	25.7%	42.5%

Notes: Data on course costs come from *Costo de los cursos para entrar a la preparatoria* (PROFECO, 2022). Household income figures are from INEGI's survey *Ingreso corriente promedio trimestral por hogar por entidad federativa y municipio 2022* (ICMM). Percentages represent the share of monthly household income required to cover the cost of a private preparatory courses for high school admission.

2.1 Elite School Admission Eligibility Restriction

Both UNAM and IPN stipulate a minimum middle school GPA of 7.0 for admission (UNAM, 2025). The policy rule is rigorous, no student with a GPA lower than seven is accepted into the elite system.[13] Although neither UNAM nor IPN have officially stated the rationale behind the policy, it is likely that this admission restriction is driven by a desire to maintain academic standards, ensure that incoming students are adequately prepared to succeed in their programs, and manage the high demand for the limited number of seats offered in their schools. With a significant number of applicants competing for a relatively small number of seats, setting higher GPA requirements helps these institutions select candidates who are most likely to excel and benefit from their academic offerings. This motivation is consistent with the evidence that insufficiently prepared students have lower chances of academic success (Denning et al., 2022; Arcidiacono et al., 2016). For elite public high schools in the Mexico City Metropolitan Area, Dustan et al. (2017) finds that a one-point decrease in middle school GPA is associated with a 17% higher probability of dropping out of high school.

2.2 Retakers

Retaking the high school entrance exam is costly. Students must allocate additional time to exam preparation for a subsequent attempt, often while attending school, and many incur monetary costs associated with preparatory courses or materials. For those already enrolled in a school, a possible switch to another school entails further costs, such as adapting to a new environment, potentially repeating coursework, and in some cases, restarting high school entirely due to non-transferable credits. Despite the associated costs, around 8.5% of students in the 2015 cohort chose to retake the exam in 2016.

Numerous factors contribute to the decision to retake, including dissatisfaction with initial matching, family relocation, or setbacks such as failing a grade or being expelled from school. These factors are not expected to change abruptly for students just above or below the middle school GPA policy threshold. The only factor that changes discontinuously at this threshold is eligibility for elite schools. Elite school eligibility influences retaking incentives through two mechanisms. On the one hand, eligible students may already have been matched with an elite school in their first attempt, diminishing the retake probability. On the other hand, students with GPAs at or above 7.0 who were not matched with an elite school in the first attempt may be more likely to retake because they are now aware of being eligible and thus have an opportunity to improve their school assignment. As a result, a discontinuity

[13] Appendix A2 provides supporting evidence that the policy operates as a sharp cutoff.

in retake behavior may emerge at the threshold, reflecting the net effect of these opposing incentives.

These competing incentives give rise to selection concerns. More motivated students may be inclined to retake the exam if they were not matched with an elite school, with the aim of improving their assignment. In contrast, the most talented students are less likely to appear among the retakers, as they likely secured admission to elite schools on their first attempt. Additionally, motivated students with a GPA below seven may choose not to retake, since the policy restricts their options to exclusively non-elite schools. Consequently, individuals who retake the examination near the eligibility threshold for elite schools may exhibit differences in unobservable characteristics.

2.3 Data

The data used in this paper include registration forms from the high school admission process, admission test scores, middle school GPAs, and ROLs for all applicants in 2015 and 2016. The registration forms encompass detailed individual-level characteristics, including demographic information, socioeconomic background, scholarship details, self-reported student behavior, and socioemotional indicators. This study concentrates on individuals retaking the COMIPEMS test, since those taking the exam for the first time lack awareness of their middle school GPA. I further restrict the analysis to students who are retaking the exam for the first time (following the original exam the previous year), thus excluding multi-year retakers, as their decisions to retake may be influenced by different factors than first-time retakers. I also exclude students affiliated with the National Institute for Adult Education (INEA), who are 18 years or older, when taking the COMIPEMS exam.[14] I exclude out-of-state students as well, as they need to reallocate in order to attend school, which may imply stronger motivation than that exhibited by local students.[15] Additionally, I exclude students who do not prioritize an elite school at the top of their ROL, since the assignment mechanism processes preferences sequentially, and listing a non-elite school first effectively removes elite options from consideration. I drop students who initially matched with an elite school, as their motive for retaking is unlikely to reflect a desire to access an elite option, since they previously secured a seat. Finally, I drop students with GPA below 7.0 who have sufficient

[14]The INEA is a federal agency in Mexico dedicated to providing basic education services to adults who did not complete their formal schooling. INEA specializes in literacy, primary, and secondary education for individuals aged 15 and older, with flexible learning models tailored to adult learners. Its programs aim to reduce educational gaps and promote social inclusion by offering free educational materials and community-based instruction.

[15]The are fewer than ten out-of-state students in the retakers population, rendering it improbable that their inclusion would significantly influence the estimations.

scores to attend an elite school, to maintain consistency with the exclusion of students above the threshold who actually were enrolled in elite schools. This last restriction ensures that the subpopulation excludes all students who could have accessed elite options regardless of their GPA, whether through actual admission or potential eligibility in the absence of the policy.

Table 4 reports the matching results for first-time COMIPEMS exam takers, all retakers, and the final subpopulation of retaker analysis. I construct a ROL type classification based on the composition of schools in each student's ROL: Elite (only elite schools), Mixed (at least one elite and one non-elite school), and Non-elite (only non-elite schools). The matching results are presented as *Matched*, students assigned by the serial-dictatorship mechanism, and *Unmatched*, students not assigned in the algorithmic round who may subsequently select from schools with available seats, as upper-secondary education is compulsory in Mexico. Table 4 shows that, in 2015, approximately 300,000 students participated in the COMIPEMS high school admission process. Of these, 25,058 retook the exam in the subsequent year, and the analyze retakers subpopulation, after applying the restrictions, comprises 20,714 individuals. Retakers concentrate their ROLs more heavily on elite schools. Among all retakers, 20.6% listed only elite schools in 2015 and 23.0% in 2016. The final retaker subpopulation is even more concentrated with 30.0% in 2015 and 33.1% in 2016, more than twice the rate for first-time takers (12.3%). Consistent with these tougher targets, assignment rates are lower for retakers: 61.6% of all retakers received a seat (58.3% in the final retaker subpopulation) versus 85.5% among first-time takers under the serial-dictatorship mechanism.

Table 4: Breakdown of Match Outcomes by ROL Type

Panel A: School Placement 2015, Exam Takers Excluding Retakers				
ROL Type	Elite	Mix	Non-elite	Total
Matched	18,284 (6.7%)	160,558 (58.5%)	55,909 (20.4%)	234,751 (85.5%)
Unmatched	15,348 (5.6%)	19,766 (7.2%)	4,565 (1.7%)	39,679 (14.5%)
Total	33,632 (12.3%)	180,324 (65.7%)	60,474 (22.0%)	274,430 (100.0%)
Panel B: School Placement 2015, retakers				
All Retakers				
Matched	145 (0.6%)	13,815 (55.1%)	1,464 (5.8%)	15,424 (61.6%)
Unmatched	5,013 (20.0%)	4,343 (17.3%)	278 (1.1%)	9,634 (38.4%)
Total	5,158 (20.6%)	18,158 (72.5%)	1,742 (7.0%)	25,058 (100.0%)
Subpopulation of Retakers				
Matched	0 (0.0%)	12,069 (58.3%)	0 (0.0%)	12,069 (58.3%)
Unmatched	4,768 (23.0%)	3,877 (18.7%)	0 (0.0%)	8,645 (41.7%)
Total	4,768 (23.0%)	15,946 (77.0%)	0 (0.0%)	20,714 (100.0%)
Panel C: School Placement 2016, retakers				
All Retakers				
Matched	3,053 (12.2%)	11,541 (46.1%)	3,313 (13.2%)	17,907 (71.5%)
Unmatched	4,465 (17.8%)	2,140 (8.5%)	546 (2.2%)	7,151 (28.5%)
Total	7,518 (30.0%)	13,681 (54.6%)	3,859 (15.4%)	25,058 (100.0%)
Subpopulation of Retakers				
Matched	2,734 (13.2%)	10,096 (48.7%)	1,606 (7.8%)	14,436 (69.7%)
Unmatched	4,130 (19.9%)	1,855 (9.0%)	293 (1.4%)	6,278 (30.3%)
Total	6,864 (33.1%)	11,951 (57.7%)	1,899 (9.2%)	20,714 (100.0%)

Notes: This table summarizes the outcomes of the school assignment process for 2015 and 2016. *Matched* refers to students assigned by the serial dictatorship. *Unmatched* denotes students not assigned by the algorithm who retain the right to enroll in another school provided seats are available, as upper-secondary education is compulsory in Mexico. The *Subpopulation of Retakers* consists of students who ranked an elite school first, did not match to an elite school initially, and satisfy the restrictions in Section 2.3. *ROL Type* classifies each student's ROL into three categories: *Elite* if the list contains only elite schools; *Mix* if it contains at least one elite and one non-elite school; and *Non-elite* if it contains only non-elite schools. Percentages in parentheses are shares of the panel total within each subtable.

3 Empirical Strategy

The objective of this study is to characterize the variation in effort exerted in exam preparation and retaking using the difference in test scores between students who are eligible to apply to elite schools and those who are not. Let T be a binary treatment indicator, where

$T = 1$ if the student is eligible for admission to an elite high school and $T = 0$ otherwise. Let R denote the running variable which in this context is the student's middle school GPA. At the known threshold $r_0 = 7$, the probability of eligibility jumps from zero to one. Let Y^* denote the true outcome of interest, which is only observed for a subset of individuals selected through a non-random process. Define Y as the observed outcome and S as a binary indicator for sample inclusion, where $S = 1$ if the individual is included in the sample and $S = 0$ otherwise. Therefore, $Y = Y^*$ when $S = 1$, and Y is missing when $S = 0$. In this setting, S indicates whether a student chooses to retake the COMIPEMS exam. Thus, $S = S_1 T + S_0(1 - T)$ gives the potential sample selection under treatment or no treatment. In addition, there is information about predetermined covariates denoted by W.

Due to the strict policy in place, all students are compliers. Thus, students possessing a GPA under seven are categorically precluded from accessing elite schools. Exploiting the discontinuity in the middle school GPA, the aim is to recover the local average treatment effect given the data on $\{Y, S, T, R, W\}$. Formally, the model is:

$$Y^* = \tau_O T + W\delta_1 + U \tag{1}$$

$$T = \mathbf{1}(R \geq r_0) \tag{2}$$

$$R = W\delta_2 + V \tag{3}$$

$$S^* = \tau_S T + W\delta_3 + E, \quad S = 1(S^* > 0) \tag{4}$$

$$Y = Y^* \cdot S \tag{5}$$

where U, V and E are error terms, δ_1, δ_2 and δ_3 are coefficients associated with W, and τ_O and τ_S are the effect of treatment T on the outcome variable and the selection term. Assuming no sample selection $\lim_{r \downarrow r} E[S \mid R = r] = \lim_{r \uparrow r_0} E[S \mid R = r]$, that is $\tau_S = 0$, and under the assumptions of the canonical RD design

A1. Discontinuity: There is a discontinuity in treatment at the cutoff.

$$\lim_{r \downarrow r_0} E[T \mid R = r] \neq \lim_{r \uparrow r_0} E[T \mid R = r].$$

A2. Smoothness: The conditional expectations of the potential outcomes are continuous at the cutoff:

$$\lim_{r \downarrow r_0} E[Y_t^* \mid R = r] = \lim_{r \uparrow r_0} E[Y_t^* \mid R = r], \quad \text{for } t \in \{0, 1\}.$$

the LATE on the outcome variable can be recovered using the observed sample as:

$$
\begin{aligned}
\lim_{r\downarrow r_0} E[Y \mid R=r] - \lim_{r\uparrow r_0} E[Y \mid R=r] = \tau_O + & \\
& \lim_{r\downarrow r_0} \sum_{w,u} (w\delta_1 + u) \Pr[W=w, U=u \mid R=r] - \\
& \lim_{r\uparrow r_0} \sum_{w,u} (w\delta_1 + u) \Pr[W=w, U=u \mid R=r] \\
= \tau_O &
\end{aligned}
$$

The model, without selection, resembles a conventional endogenous variable configuration, but with an observed assignment variable R. Moreover, W can be determined endogenously, provided that it is realized before V, so there is randomization at the cutoff r_0. Intuitively, the requirement for the RD design is that students do not have full control over their GPAs. Within this framework, the variation in outcomes among individuals is entirely characterized by the random variables (W,U). Consequently, individuals who exhibit identical values of (W,U) will experience one of two possible outcomes, contingent upon receiving treatment. There is no stance as to whether some elements of δ_1 or δ_2 are zero, since there is not need for exclusion restriction under the RD design.

However, if there is sample selection $\lim_{r\downarrow r_0} E[S \mid R=r] \neq \lim_{r\uparrow r_0} E[S \mid R=r]$, then $\tau_S \neq 0$. The LATE cannot be estimated using the observed sample. That is $\tau = \lim_{r\downarrow r_0} E[Y^* \mid R=r] - \lim_{r\uparrow r_0} E[Y^* \mid R=r] \neq \lim_{r\downarrow r_0} E[Y \mid R=r] - \lim_{r\uparrow r_0} E[Y \mid R=r]$. Given that $\lim_{r\downarrow r_0} \sum_{w,u}(w\delta_1+u)\Pr[W=w, U=u \mid R=r] \neq \lim_{r\uparrow r_0} \sum_{w,u}(w\delta_1+u)\Pr[W=w, U=u \mid R=r]$. Even if the distribution of observables W is smooth at the cutoff, discontinuities in the selection process can still generate differences in the distribution of unobservables U. In other words, balance in predetermined covariates does not guarantee valid identification if the probability of being observed changes at the cutoff.

The credibility of $\lim_{r\downarrow r_0} E[S \mid R=r] = \lim_{r\uparrow r_0} E[S \mid R=r]$ is challenged in this context due to self-selection.[16] Specifically, I only observe outcomes for students who opt to

[16] A general approach to estimate sample selection is using a fuzzy RD Wald ratio:

$$
\tau_S = E[S_1 - S_0 \mid R=r_0, C] = \frac{\lim_{r\downarrow r_0} E[S \mid R=r] - \lim_{r\uparrow r_0} E[S \mid R=r]}{\lim_{r\downarrow r_0} E[T \mid R=r] - \lim_{r\uparrow r_0} E[T \mid R=r]}.
$$

In this case, treatment T switches deterministically at the cutoff middle school GPA equal to seven. The denominator equals one and the estimand reduces to a sharp RD design.

retake the COMIPEMS exam, with this decision being endogenous. Such endogeneity may result in differences between the student populations on either side of the GPA threshold. Methodologies dealing with sample selection employ some correction (e.g., Heckman, 1979 and Heckman, 1990) that relies on an exclusion restriction, which may be questionable in the RD design context, when there is a jump in both the selection and the outcome variables at the running variable discontinuity.

To address self-selection in this empirical setting, I implement a series of econometric approaches within the regression discontinuity (RD) framework, summarized in Table 5. These approaches differ in their identification assumptions and target estimands. As a baseline, I estimate the canonical RD design (Hahn et al., 2001), which does not explicitly address selection. To restore smoothness, I adopt the first-difference specification that subtracts from the outcome variable its lagged value (Lee and Lemieux, 2010). Finally, to quantify whether the effects remain statistically significant under potential selection, I employ the sharp bounds on the local average treatment effect (LATE) developed by (Dong, 2019). I also consider approaches that depart from the smoothness condition. These alternative methods rely on the assumption of unconfoundedness, enabling the estimation of conditional average treatment effects (CATE) either by adjustment for observable characteristics using machine learning techniques (Athey et al., 2019), or by accounting for unobserved characteristics via a proxy variable (Dale and Krueger, 2014). An exposition of each model follows in detail.

Table 5: Summary of RDD Models, Conditions, and Effect Estimates

RD Design	**Continuity**[1]	**Other Condition**	**Target Effect**	**Assumption Source**
Canonical	$E[Y_t^* \mid r]$	Continuity $E[S_t \mid r_0]$	LATE	Hahn et al. (2001)
Gains	$E[\Delta Y_t \mid r]$	No anticipatory behavior	LATE	Lee and Lemieux (2010)
Selection	$E[(Y_t^*, S_t) \mid r]$	—	LATE Bounds	Dong (2019)
Observables	—	Unconfoundedness	CATE	Athey et al. (2019)
Unobservables	—	Unconfoundedness	CATE	Dale and Krueger (2014)

[1] Continuity refers to the assumption that the conditional expectation of potential outcomes is continuous at the threshold r_0 of the running variable. For instance, for the canonical RD design, $E[(Y_t^*) \mid r]$ implies $\lim_{r \downarrow r_0} E[Y_t^* \mid R = r_0] = \lim_{r \uparrow r_0} E[Y_t^* \mid R = r_0]$ for $t \in \{1, 0\}$.

Gains model. The gains model estimates the LATE using the difference in test scores as the outcome variable. This approach is based on the insight that if the lagged outcome is determined prior to treatment assignment (i.e., before the realization of the running variable R), then subtracting the lagged outcome from the current outcome, $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$, restores smoothness on the outcome variable (Lee and Lemieux, 2010). This strategy may be problematic if students engage in anticipatory behavior, adjusting their effort in response to expected elite school eligibility based on prior academic performance, since this would render the lagged outcome endogenous and lead to biased estimates.[17] As noted in the literature, lagged specifications tend to outperform gains ones in value-added estimations (Andrabi et al., 2011; Guarino et al., 2015; McCaffrey et al., 2009). In the results section 4, I include both gains and lagged specifications due to their conceptual similarity. However, it is only the former that restores smoothness.

Sample Selection model. The model deals with both endogeneity of treatment and sample selection (Dong, 2019). The identification relies on smoothness $E(Y_t^*, S_t|r)$ condition for the entire population and does not require specifying any selection mechanism. Under this assumption, the observed sample selection $S = S_0 + T(S_1 - S_0)$ is allowed to jump at the threshold r_0. The model separates the policy impact into two components, the extensive margin, which reflects changes in the probability of retaking the exam, and the intensive margin, which captures changes in test scores. Formally, the extensive margin effect is defined as $E[S_1 - S_0 \mid R = r_0]$ and the intensive margin effect is expressed as $E[Y_1^* \mid S_1 = 1, R = r_0] - E[Y_0^* \mid S_0 = 1, R = r_0]$.

While the intensive margin effect identifies the change in outcomes for students who retake the exam, this estimate may still be confounded by selection into retaking. To address this issue, bounds on the intensive margin can be constructed under the assumption of monotonic selection, which requires that treatment can exclusively affect sample selection in one direction. In this case, students with a GPA less than seven are less likely to retake the exam than those at or above seven $Pr(S_1 \geq S_0) = 1$. The bounds are sharp and fall into the class of *worst case* bounds scenario (Horowitz and Manski, 1995). In our data, monotonic selection is expected to hold for students with insufficient test scores to be matched to an elite school in their initial application.[18]

The next models relax the continuity assumption and instead rely on unconfoundedness $Y_0, Y_1 \perp T \mid W$ (Rosenbaum and Rubin, 1983). Conditional on covariates W, the treatment assignment is as good as random. Under this assumption, I use the covariate adjusted

[17] In this context, anticipatory effort exerted in earlier grades in expectation of eligibility may invalidate the assumption that the lagged outcome is predetermined.

[18] Under monotonic selection, with probability one, selection into retaking under eligibility for elite schools is at least as high than under non-eligibility. This holds after excluding students who were matched to an elite school on their first attempt in 2015, as these students are empirically less likely to retake (see Table 6).

difference between the two treatment groups, $E[Y_1 \mid T = 1, W] - E[Y_0 \mid T = 0, W]$, to estimate the Conditional Average Treatment Effect (CATE). Without assuming continuity of potential outcomes in the running variable or the absence of endogenous sorting at the cutoff, this framework does not recover a LATE at the threshold. Instead, it recovers a conditional treatment effect. As such, the estimand under unconfoundedness assumption lacks the clear quasi-experimental interpretation associated with an RD design. Nevertheless, by leveraging rich covariate information, this approach offers a flexible and policy-relevant alternative when the assumptions of traditional RD design are violated.

Model based on observables. Given the high dimensionality and richness of the available covariates, I implement random forests to estimate conditional average treatment effects (CATE), using the linear forest approach. The model controls for a comprehensive set of sociodemographic variables (e.g., income, mother's education, access to goods and services), behavioral (e.g., task prioritization, adherence to deadlines) and psychological variables (e.g., feelings of depression, aggressiveness). Athey et al. (2019) employ this method to identify heterogeneous treatment effects across subpopulations. In contrast, I use it to control for a large set of variables and obtain the average estimate for the retakers subpopulation within the bandwidth.

Model based on unobservables. This model controls for the unobserved ability of students, since a positive bias may arise because more ambitious or motivated students, with higher unobserved ability, are more likely to opt into retaking. By controlling for unobserved ability through a proxy variable, such as the proportion of elite schools in the student's ROL, I address the selection problem that arises from omitted variable. This strategy relies on the idea that students' revealed preferences embed information about latent traits such as ambition, expectations, or private knowledge of ability. Similar to other settings where admission processes are leveraged to address selection on unobservables, incorporating preference data allows to proxy for these latent characteristics and mitigate bias in the estimated effects (Dale and Krueger, 2014).

3.1 Estimation

Estimates are based on first-order local linear polynomials. The treatment effect at the cutoff is obtained by fitting separate weighted regressions on either side of the running variable threshold and taking the difference in intercepts. A triangular kernel is used to place greater weight on observations closer to the threshold, and bandwidths are selected using mean-squared error (MSE) optimal rules with robust bias correction to ensure valid inference.

Higher-order local polynomials are not employed, as they often generate noisy estimates and result in poor confidence interval coverage (Gelman and Imbens, 2019; Kolesár and Rothe, 2018).[19]

Following Calonico et al. (2014), τ_{RD} is estimated using local polynomial regression with kernel weights for a generic outcome $\tilde{Y}$ (e.g., Y or S). For each side of the cutoff r_0, the local linear estimator solves[20]

$$\hat{\beta}_{+}(h) = \arg\min_{\alpha,\beta} \sum_{i:R_i \geq r_0} \left(\tilde{Y}_i - \alpha - \beta(R_i - r_0)\right)^2 K_h(R_i - r_0),$$

$$\hat{\beta}_{-}(h) = \arg\min_{\alpha,\beta} \sum_{i:R_i < r_0} \left(\tilde{Y}_i - \alpha - \beta(R_i - r_0)\right)^2 K_h(R_i - r_0),$$

where $K_h(u) = K(u/h)/h$ is a rescaled kernel function with bandwidth h and $K(\cdot)$ is the triangular kernel. Due to recentering, the fitted values at the cutoff are given by

$$\hat{\mu}_{+}(r_0) = \hat{\alpha}_{+}, \qquad \hat{\mu}_{-}(r_0) = \hat{\alpha}_{-},$$

and the RD estimator is

$$\hat{\tau}_{\text{RD}} = \hat{\mu}_{+}(r_0) - \hat{\mu}_{-}(r_0).$$

Because local polynomial estimators at boundaries are biased, Calonico et al. (2014) propose a bias-corrected estimator. The leading bias is estimated using a higher-order polynomial for both estimations.

$$\hat{\tau}_{\text{BC}} = \hat{\tau}_{\text{RD}} - \hat{B},$$

where $\hat{B}$ is the estimated bias. Robust inference is then based on

$$CI_{\text{RBC}}: \quad \hat{\tau}_{\text{BC}} \ \pm \ z_{1-\alpha/2} \cdot \widehat{\text{SE}}_{\text{RBC}}.$$

I re-estimate the models by dropping students with middle school GPA of 7.0 to control for potential heaping using the donut RD design approach (Almond et al., 2010). Heaping might occur if some students are able to negotiate a GPA of 7.0, even when their grades were lower. The main reason heaping is not expected is that the GPA in middle school is the average of the grades obtained in each subject in middle school. Each teacher in

[19] Gelman and Imbens, 2019 advice against using higher order than second polynomial. I don't use second order polynomial since the variable is too coarse.

[20] Covariates are added for estimations based on observables and unobservables.

middle school submits their grades individually, and then these grades are averaged by a system. For a student to manipulate the system, the average GPA must be consistent with the entire set of grades submitted.[21] To do so, a student would likely need to convince several teachers and possibly even the principal to rig the system. Although I do not entirely dismiss the possibility of such manipulation, I believe that it is unlikely to occur. Nevertheless, I re-estimate the RD design by excluding students who are exactly at the 7.0 cutoff.

4 Results

This section first examines how the middle school GPA policy induces self-selection, then presents the results on effort, measured as the difference in test scores between students deemed eligible and those deemed ineligible for admission to elite institutions.

4.1 Self-Selection

The middle school GPA policy for elite high school eligibility operates through two channels with respect to retaking: (i) among students eligible to attend elite schools, those who had been initially matched to an elite school exhibit a lower probability of retaking the exam; and (ii) among students who are eligible but not initially admitted to elite schools, have higher probability of retaking relative to otherwise similar students who are not eligible to apply to elite schools. Taken together, these patterns show a discontinuous change in selection at the relevant middle school GPA threshold $\lim_{r \downarrow r_0} E[S \mid R = r] \neq \lim_{r \uparrow r_0} E[S \mid R = r]$. The policy is expected to generate monotonic selection for students with insufficient test scores to be matched in their first attempt to elite schools. A student, under treatment, is weakly more likely to retake the exam $Pr(S_1 \geq Pr(S_0)) = 1$ than without treatment. The monotonicity condition is necessary to estimate sharp bounds for the effort LATE (Dong, 2019).[22]

4.1.1 Elite Admissions under First Attempt and the Probability of Retaking

I inspect whether having a sufficient test score to be matched to an elite school in the first attempt affects next year retaking probability for elite schools eligible and ineligible students. For that purpose, I first construct a variable denoted distance to least-preferred elite school

[21] Appendix A3 contains detailed information about middle school grading system.

[22] The monotonic condition aligns with the construction of the retakers subpopulation, for details see subsection 2.3.

(DLP) that measures the distance between each student's least preferred elite school cutoff and her observed test score. Formally, for each student i, let the ROL be:

$$\text{ROL}_i \;=\; (s_{i1}, s_{i2}, \ldots, s_{iJ}), \quad s_{i1} \succ s_{i2} \succ \cdots \succ s_{iJ},$$

where s_{ij} is student's i j-th preferred school. Let $\mathcal{E}$ denote the set of elite schools, and c_s school s first attempt admission cutoff. Define student i least preferred elite option as

$$s_i^L \;\equiv\; \arg\min_{\succ}\{\, s_{ij} \in \text{ROL}_i : s_{ij} \in \mathcal{E} \,\},$$

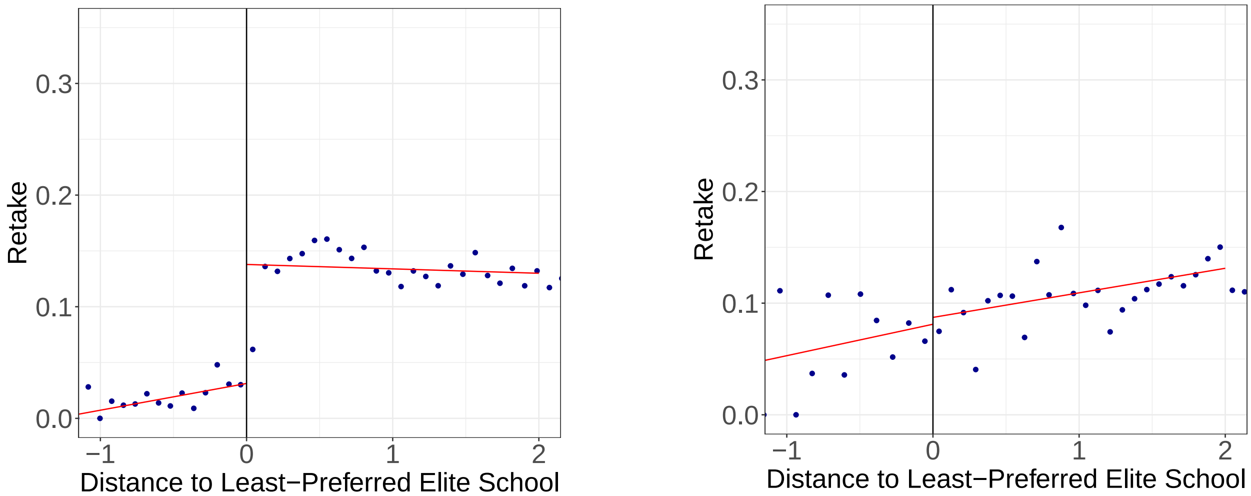
and let $c_{s_i^L}$ be the corresponding first attempt s_i^L school cutoff. The variable of interest for each student i is defined as:

$$DLP_i = c_{s_i^L} - TS_i,$$

where TS_i is student's i first attempt COMIPEMS test score. Thus, $DLP_i \leq 0$ indicates that TS_i meets or exceeds the cutoff of student's i least-preferred elite school, whereas $DLP_i > 0$ indicates the student fall short to be matched to a elite school in her ROL. Students with a GPA less than seven ($\text{GPA}_i < 7$) remain ineligible for elite admission regardless of their DLP_i value.

Figure 4a shows the relationship between retake probability and DLP for students eligible for elite school ($GPA \geq 7$). There is a discontinuity in retake at 0, which can be interpreted as students admitted to elite schools being less likely to retake the COMIPEMs exam, compared with marginally rejected students. In contrast, Figure 4b, which presents the same relationship for students who are ineligible for elite schools ($GPA_i < 7$), does not reveal a discontinuity in retake behavior around zero. This last figure shows that the retake behavior of elite school ineligible students is influenced exclusively by unrelated admission factors to admission to elite schools, as expected. Thus, the probability of retaking behaves smoothly around the eligibility threshold.

To formally estimate the effect of admission to an elite school at the initial attempt on the probability of retaking the COMIPEMS exam of students, I estimate an RD design model using the DLP running variable and evaluating the jump in the probability of retaking at zero. I estimate two separate models: one for students deemed eligible under the policy rule and another for those who are not. Table 6 reports the results. In 2015, admission to an elite school for elite eligible students reduces the probability of retaking by 10.3 pp, while no effect is observed for ineligible ones. The results are consistent with the notion that highly motivated or talented students are already matched to elite schools and thus are less likely to retake.



(a) Students with GPA ≥ 7

(b) Students with GPA < 7

Figure 4: Retake Probability by Distance to Least-Preferred Elite School

Notes: This figure plots the probability of retaking in 2016 against the *distance to least-preferred elite school* variable. A negative *distance to least-preferred elite school* indicates a test score that is sufficient for elite school admission. A positive indicates a insufficient test score for elite school admission. Panel (a) focuses on students with $GPAs \geq 7$. Panel (b) presents results for students with $GPAs < 7$.

Table 6: LATE of Initial Elite Matching on Retake Probability

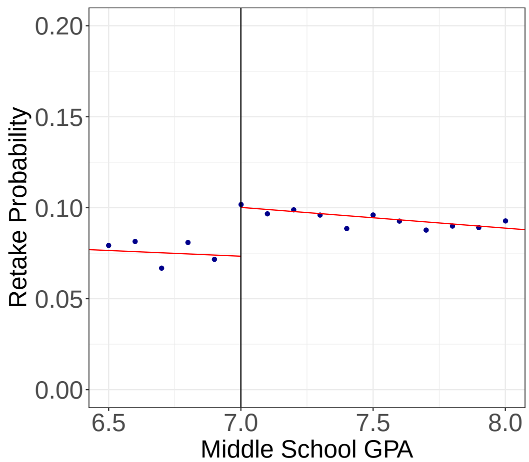
	Eligible (GPA $\geq$ 7.0)	Ineligible (GPA $<$ 7.0)
	(1)	(2)
τ_S	0.103***	0.011
SE	0.012	0.037
Bandwidth (h)	0.33	0.53
Bias (L - R)	0.001 – 0.004	0.001 – 0
Obs. (L - R)	1,855 – 2,971	309 – 812

Notes: The table reports the LATE of having a sufficient test score to be admitted into a elite school on retake probability. Standard errors (SE) are robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

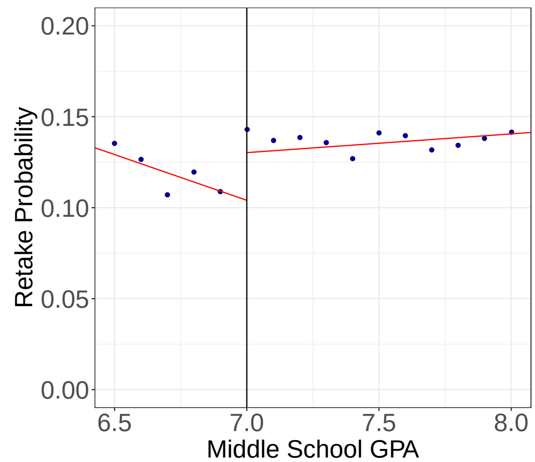
4.1.2 Probability of Retaking and Middle School GPA

To assess whether eligibility for elite schools affects the probability of retaking the COMIPEMS exam, I explore retake behavior at the middle school GPA policy. Figure 5a shows that the probability of retaking the COMIPEMS exam exhibits a discontinuity at 7.0 GPA. At 7.0 GPA, approximately 10% of the students retake the exam, compared to 7.5% with a 6.9

GPA, equivalent to a 2.5 pp increase for students eligible for elite schools. The discontinuity reflects the combined influence of two opposing mechanisms: students matched with elite schools on their first attempt are less likely to retake, while elite school eligible students who were not previously matched with an elite school are more likely to retake with the intention of securing a seat at an elite school. To isolate the latter effect, Figure 5b drops students with sufficient test scores to be matched to elite schools on their first attempt, that is, students with $DLP \leq 0$. After dropping these students, the discontinuity persists, with close to 12.5% of students at 7.0 retaking the exam, compared to 10% at 6.9 a difference of the same magnitude.



(a) All students



(b) Students with $DLP_i > 0$

Figure 5: Regression Discontinuity Results for 2016

Notes: This figure shows regression discontinuity results relating middle school GPA to the probability of retaking the COMIPEMS exam. Panel A plots all students, while Panel B restricts the sample to retakers who did not achieve sufficient test scores to access elite schools in their first opportunity $DLP > 0$.

To formally quantify the change in retake probability, I estimate the impact of the middle school GPA policy and evaluate whether a discontinuity arises at the eligibility threshold. Table 7 reports the results. Column (1) presents the estimates for all students, indicating a 3.0 pp increase in the probability of retaking. Given a baseline probability of retaking at the policy cutoff of 10 percent, this effect corresponds to a 30 percent higher probability of retaking for students with the opportunity to attend elite schools. This effect reflects both the influence of prior elite school assignment, which affects students' incentives to retake, and the policy induced eligibility at the 7.0 GPA threshold. Column (2) reports results for students with $DLP_i > 0$, which excludes all students with sufficient test scores to be matched with elite schools the first time they applied. For this subpopulation, the RD design isolates the causal effect of eligibility on retaking without contamination from prior elite school assignment. The estimated effect is 3.4 pp, which is consistent with the notion that prior assignment to an elite school lowers the incentive to retake. Relative to the same baseline retake probability of 10 percent, this effect implies an increase of 34 percent for students eligible to attend elite schools derived from the middle school GPA policy.

The findings indicate that self-selection in retaking is a concern around the GPA policy threshold, as it reshapes students' retaking incentives. Without information on how students make and act upon retaking decisions, it is not possible to determine composition differences on either side of the threshold. While differences in observable characteristics are testable, unobserved factors such as motivation or aptitude may not be, rendering RD design effort estimates based on the observed retaker population potentially biased.

Table 7: LATE of Middle School Policy on Retake Probability

	All Students (1)	Student with $DLP_i > 0$ (2)
τ_S	0.030***	0.034***
SE	0.005	0.009
Bandwidth (h)	0.43	0.41
Bias (L - R)	0.001 – 0	-0.001 – 0
Obs. (L - R)	23,974 – 55,801	10,128 – 30,844

Notes: The table reports the LATE of being eligible to attend an elite school on retake probability. Standard errors (SE) are robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2 Effort and Test Scores

This section begins by presenting graphical evidence that eligibility for elite schools may incentivize students to increase their effort on the COMIPEMS entrance exam. First, I document a discontinuity in test scores at the middle school GPA eligibility threshold among students who retake the exam in 2016, which is not present for the same student the previous year. The remainder of the section introduces a series of RD designs. First, I estimate the canonical RD design that assumes no selection. The framework is then extended to account for endogenous retake decisions by implementing models that adjust for sample selection, as well as approaches that relax the continuity assumption and rely on observable and unobservable characteristics.

4.2.1 Preliminary Evidence on Effort

This subsection provides preliminary visual evidence on effort disparities between elite school eligible and ineligible students at the policy threshold. The analysis plots the running variable alongside COMIPMES test scores, normalized to have mean zero and standard deviation one. In line with the limited time available for students to adjust their efforts, the graphical inspection of students who took the COMIPEMS exam only once, in 2015, shows no visible discontinuity in the test scores at the elite school eligibility GPA threshold (Figure 6). he same absence of discontinuity is observed when examining the outcome of the first attempt at the exam by students who will eventually retake it, both for the full set of retakers (Figure 7a) and for the restricted population of retakers (Figure 8a). In contrast, in the following year, there is a discontinuity around the 7.0 middle school GPA threshold, indicating that students who retake the exam and have GPA at or marginally above 7.0 (hence eligible to attend an elite school) generally outperform those whose GPA is marginally below 7.0 and who therefore lack the opportunity (Figure 7b and Figure 8b). The graphical evidence indicates that elite school eligibility is associated with higher test scores. However, this relationship may be partly driven by self-selection into retaking the exam.

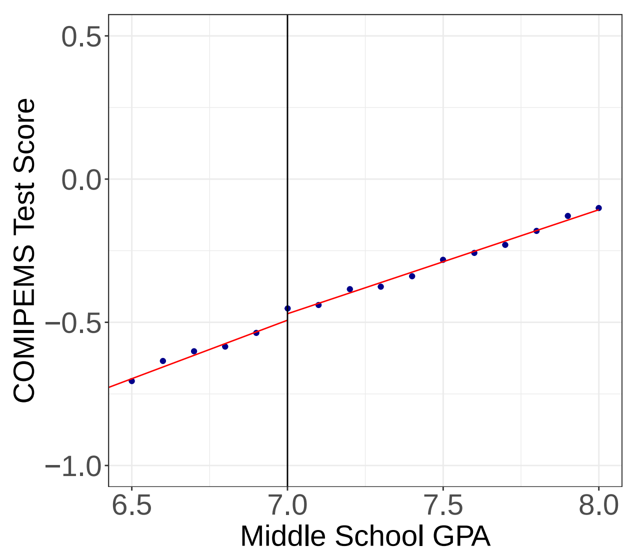
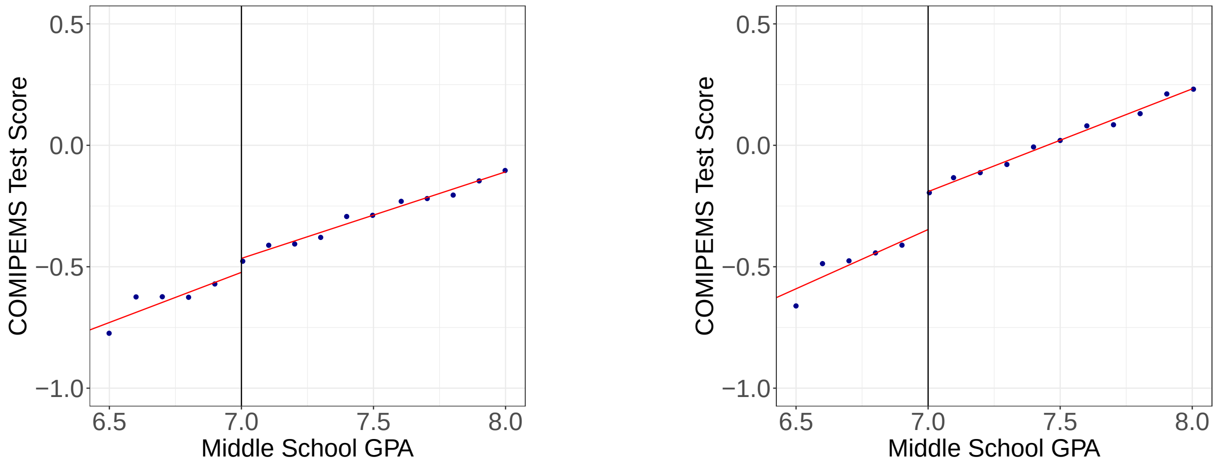


Figure 6: Discontinuity on Test Scores

First-time Takers, 2015

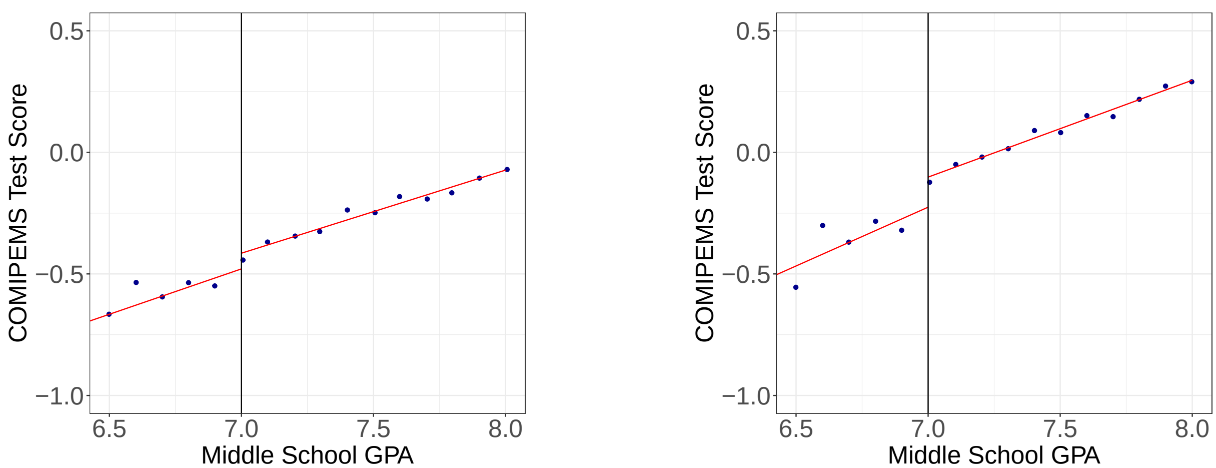
Notes: This figure displays the results from first-order local polynomial regressions, with middle-school GPA on the horizontal axis and normalized COMIPEMS entrance exam scores on the vertical axis.



(a) 2015 (b) 2016

Figure 7: Discontinuity on Test Scores
All Retakers

Notes: This figure displays the results from first-order local polynomial regressions, with middle-school GPA on the horizontal axis and normalized COMIPEMS entrance exam scores on the vertical axis. Panel (a) includes the all retakers in 2015, while Panel (b) show the results for the all retakers in 2016.



(a) 2015 (b) 2016

Figure 8: Discontinuity on Test Scores on the Retakers Subpopulation

Notes: This figure displays the results from first-order local polynomial regressions, with middle-school GPA on the horizontal axis and normalized COMIPEMS entrance-exam scores on the vertical axis. Panel (a) includes the restricted subpopulation of retakers in 2015, while Panel (b) show the results for the same subpopulation in 2016.

4.2.2 Canonical RD design

Table 8 shows the results of the canonical RD design for the restricted subpopulation. In line with the limited time for students to adjust effort in the entrance exam, since they are unaware of their middle school GPA, for year 2015 there are no significant differences in test scores between eligible and ineligible students at the policy threshold. In contrast, in 2016, where retakers are fully aware of their GPA, estimates indicate a positive and significant impact of the policy on test scores. Students eligible for elite schools scored 0.23 and 0.25 standard deviations higher than those just below, respectively, for the standard and donut estimates.

Table 8: LATE on COMIPEMS Scores

	RDD 2015		RDD 2016	
	Standard	Donut	Standard	Donut
	(1)	(2)	(3)	(4)
τ_O	0.077	0.095	0.229**	0.245**
SE	0.101	0.116	0.104	0.119
Bandwidth (h)	0.41	0.38	0.41	0.39
Bias (L - R)	0.013 – 0.003	0.016 – -0.011	0.058 – 0.003	0.052 – 0.003
Obs. (L - R)	1,154 – 4,192	979 – 2,566	1,149 – 4,189	973 – 2,563

Notes: This table reports the canonical RD design results. The estimates are computed for the restricted subpopulation. Donut specifications exclude observations with a 7.0 middle school GPA. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2.3 Difference and Lag Specification

The difference and lag specifications adjust for student heterogeneity by taking into account prior academic performance. This approach helps ensure that the observed effects of the policy are not confounded by pre-existing disparities in student ability. Table 9 shows that, according to the difference specification, students just above the GPA threshold scored 0.10 and 0.09 standard deviations higher than those just below, in the standard and donut estimations, respectively. The lag specification yields similar results, with estimated impacts of 0.12 and 0.09 standard deviations. The difference and lag specifications provide estimates of gains in test scores by adjusting for baseline performance, the earlier results reported in Table 8 do not account for prior achievement and instead capture level differences. These level estimates, which range from 0.23 to 0.25 standard deviations in 2016, are larger than the gain estimates. The difference in magnitude reflects that the level specifications conflate the policy effect with potential differences in baseline ability. In contrast, the gain estimates provide an unbiased measure of the policy-induced improvement in performance, isolating the extent to which students increased their academic effort as a response to being eligible for elite schools, if no anticipatory behavior takes place.[23]

Table 9: LATE on COMIPEMS Scores
(2016, differences and lag)

	Diff		lag	
	Diff	Diff Donut	Lag	Lag Donut
	(1)	(2)	(3)	(4)
τ_O	0.102**	0.091*	0.115***	0.086*
SE	0.045	0.051	0.044	0.05
Bandwidth (h)	0.38	0.38	0.38	0.38
Bias (L - R)	0.032 – 0	0.035 – 0.016	0.035 – 0	0.037 – 0.014
Obs. (L -R)	973 – 3,339	973 – 2,563	973 – 3,339	973 – 2,563

Notes: This table reports the estimates from a RD design using two alternative specifications. In the difference specification, the outcome variable is the difference in test scores. In the lag specification, the outcome variable is the 2016 test score, and the lagged test score is included as a covariate. The estimates are computed for the restricted subpopulation. Donut specifications exclude observations with a 7.0 middle school GPA. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2.4 Sample Selection

Table 10 reports the RD design estimates that address selection bias, identifying the extensive and intensive margin impacts of the policy (Dong, 2019). For the restricted subpopulation, the extensive margin estimate is 2.6 pp, indicating that the GPA policy increases the probability of retaking for elite school eligible students, and the intensive margin estimate is 0.23 standard deviation, consistent with the idea that students who gain the possibility of attending an elite school exert greater effort, the intensive margin estimate is 0.23 standard deviations. Under the monotonicity assumption, the corresponding sharp bounds range from nearly zero to 0.37 standard deviations, implying that the policy has a positive effect on effort even after accounting for potential selection into retaking. Donut RD estimates provide similar results.

[23] When comparing test-score differences, the distribution of gains for students eligible for elite schools lies to the right of that for ineligible students; see Appendix A4 for density plot.

Table 10: Extensive and Intensive Margins at the Cutoff

	Standard (1)	Donut (2)
$\Pr(S_0 = 1 \mid R = r_0)$	0.104***	0.100***
	(0.012)	(0.013)
$\Pr(S_1 = 1 \mid R = r_0)$	0.129***	0.127***
	(0.003)	(0.004)
Extensive margin (τ_S):	0.026	0.027
	(0.018)	(0.019)
$E[Y_0 \mid S_0 = 1, R = r_0]$	−0.413***	−0.410***
	(0.098)	(0.102)
$E[Y_1 \mid S_1 = 1, R = r_0]$	−0.181***	−0.174***
	(0.021)	(0.024)
Intensive margin (τ_O):	**0.232**	**0.236**
	(0.131)	(0.137)
Intensive Margin Bounds		
Lower bound:	0.004	0.005
Upper bound:	0.366	0.370

Notes: The table shows RD design estimations of the extensive margin, the increase in the probability of retake, and intensive margin, the increase in test scores. The intensive margin point estimate assumes no sample selection. Intensive margin bounds are built assuming monotonic selection. The donut specification exclude students with a 7.0 middle school GPA. Standard errors (SE) in parentheses are calculated using bootstrap resampling. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2.5 Controlling for Observables

The admission process questionnaire contains a wide range of questions. I take an agnostic view and include all of them to fit the linear models (Athey et al., 2019). The confidence intervals are obtained via bootstrap by resampling the data with replacement to estimate the distribution of the LATE. The results indicate a median increase of 0.10 standard deviation (0.12 for the donut estimates) in the test scores of students to the right of the middle school GPA threshold compared to those to the left. The 95% confidence interval ranges from 0.05 to 0.13 standard deviations (0.07 to 0.14 under the donut specification).

4.2.6 Controlling for Unobservables

Table 11 presents the results of the regression discontinuity analysis controlling for unobservable student characteristics by including as a covariate the proportion of elite schools to which students apply. The LATE coefficient corresponding to the 2015 estimates lacks statistical significance, which is consistent with prior findings. In contrast, the 2016 estimates remain significant. Incorporating the proportion of elite schools in students' ROLs mitigates the impact of the middle school GPA policy from 0.229 and 0.245 for the standard and donut estimates (Table 8) to 0.179 and 0.155 (Table 11), respectively. The results indicate that unobserved student characteristics account for part of the observed variation in test scores. Including the proportion of elite schools in students' ROLs may correct otherwise biased estimates.[24]

Table 11: CATE on COMIPEMS Scores
(controlling for unobservables)

	RDD 2015		RDD 2016	
	Standard	Donut	Standard	Donut
	(1)	(2)	(3)	(4)
τ_O	0.069	0.084	0.179***	0.155**
SE	0.063	0.074	0.069	0.078
Bandwidth	0.56	0.58	0.6	0.61
Bias	0.018 – 0.001	0.018 – -0.001	0.054 – 0.001	0.053 – 0.014
Obs.	1,154 – 4,192	979 – 2,566	1,149 – 4,189	973 – 2,563

Notes: This table reports the regression discontinuity results controlling for the proportion of elite schools listed in the rank-order. The estimates are computed for the restricted subpopulation. Donut specifications exclude students with a 7.0 middle school GPA. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.3 Changes in Admissions to Elite school

Admission processes in many educational settings are often difficult to characterize, as they typically depend on multiple criteria such as test scores, essays, interviews, and recommendation letters. In contrast, the centralized assignment algorithm used in the case under consideration provides a clear and rule-based decision mechanism, allowing for a transparent simulation of counterfactual admissions outcomes and a close approximation of the number of students who would have gained admission under alternative effort scenarios.

To estimate the proportion of students who would have been admitted to elite schools even in the absence of effort induced by elite school eligibility, I simulate the serial dictatorship mechanism 100 times using the estimated effect from the RD estimations. The counterfactual test scores are changed exclusively for retakers with middle-school GPAs at or above 7.0.

[24]Including the proportion of elite schools students listed in 2015 as a covariate decreases the LATE coefficient on the retaking probability by roughly half, from 0.030 to 0.017. Including covariates, such as mother and father educational level, student highest desired educational level, university the student desires to attend (e.g., UNAM, IPN, private, etc.), and fallback options in the event of rejection from a preferred institution, does not yield an impact in the LATE coefficient.

The simulated outcome is defined as

$$Y_{i0}^{(s)} = Y_{i1} - \tau_O - \varepsilon_i^{(s)}$$

where Y_{i1} is the realized outcome for eligible to elite school retakers, τ_O denotes the estimated treatment effect, and $\varepsilon_i^{(s)} \sim \mathcal{N}(0, \mathrm{Var}(\tau_O))$ captures random variation in the estimate across simulations $s = 1, \ldots, 100$. The serial dictatorship algorithm is re-run for each simulated draw to compute the proportion of eligible retakers who would have been admitted to elite schools under the counterfactual scenario without the estimated effect.

Let μ denote the realized matching, and for each simulation draw $s = 1, \ldots, S$ (with $S = 100$) let $\mu^{(s)}$ be the matching produced by re-running the serial dictatorship on the counterfactual outcomes. Define the set of eligible retakers

$$\mathcal{R} \;\equiv\; \{\, i : \text{retaker},\ \text{GPA}_i \geq 7 \,\}, \quad n_{\mathcal{R}} = |\mathcal{R}|,$$

and let $\mathcal{E}$ be the set of elite schools. For each $i \in \mathcal{R}$ and draw s, define the counterfactual elite-admission indicator

$$A_i^{(s)} \;\equiv\; \mathbf{1}\{\, \mu^{(s)}(i) \in \mathcal{E} \,\}\,.$$

The simulated proportion of eligible retakers admitted to elite schools in draw s is

$$\widehat{p}^{(s)} \;=\; \frac{1}{n_{\mathcal{R}}} \sum_{i \in \mathcal{R}} A_i^{(s)} \;=\; \frac{1}{n_{\mathcal{R}}} \sum_{i \in \mathcal{R}} \mathbf{1}\{\, \mu^{(s)}(i) \in \mathcal{E} \,\}\,.$$

Aggregating across simulations yields:

$$\widehat{p} \;=\; \frac{1}{S} \sum_{s=1}^{S} \widehat{p}^{(s)}$$

Table 12 shows the result of the conterfactual simulations. In the observed matching, 28.4% of the retaker subpopulation with GPAs at or above seven were admitted to elite schools. When the estimated treatment effect from the canonical RD specification is removed, the implied counterfactual proportion decreases to 18.8%, suggesting that roughly 9.6 pp of elite admissions can be attributed to effort induced by eligibility. Under the gains and observables specifications, the estimated effort increases admission by 4.9 pp and 5.2 pp, respectively. Accounting for unobservable characteristics has an effect of 8 pp in admission to elite schools. Overall, these simulations indicate that a 0.10 sd increase is equivalent to an increase of 5 pp increase in elite admission for retakers.[25]

Table 12: Counterfactual Simulation of Elite-School Matches after Subtracting Effort Effects

	τ_O	Proportion Accepted (%)	Change (pp)
Observed (Baseline)	–	28.4	–
Canonical RDD	0.23	18.8	9.6
Gains	0.10	23.5	4.9
Observables	0.10	23.2	5.2
Unobservables	0.18	20.4	8.0
Bounds[1]			
Lower-Upper	0.00-0.37	28.4-12.1	0 - 16.3

Notes: Counterfactual proportions are derived from 100 simulations of the serial dictatorship algorithm for elite-school admissions.

[1] Sharp bounds estimates are simulated once, as their sampling variance is not computed.

5 Validity

This section examines, for the restricted subpopulation, the validity of the RD design by testing for discontinuities in predetermined covariates at the policy threshold, the lack of significant LATE effects at placebo middle school GPAs, continuity of the running variable, and the null impact among students who did not express interest in elite schools, as these students should not present changes in test scores at the middle school policy threshold. Although evidence of sample selection motivates the need for methods to address it, establishing the credibility of the RD design still requires standard validity checks.

5.1 RD design on Covariates

Table 13 reports the RD design estimates for a rich set of predetermined covariates at the seven middle school GPA threshold. The analysis covers three categories: student behavior, sociodemographic factors and scholarships, and goods and services. In the student behavior category, variables such as priority order, adherence to deadlines, ability to set priorities, and anticipation yield not significant coefficients. In the sociodemographic and scholarship category, most covariates, including perceived socioeconomic status, mother's education, and

[25] Applying the same shift τ_O to all eligible retakers, including those far from the bandwidth, imposes a constant treatment extrapolation. If instead the adjustment were applied only within the bandwidth, it would mechanically introduce a jump in the counterfactual score distribution at the point where the adjustment stops. To avoid such artifacts, we apply a uniform test score change to all retakers with GPAs equal or greater than seven.

scholarship receipt, show no evidence of discontinuity, while father's education exhibits a statistically significant effect. In the goods and services category, most items, such as the number of televisions and vacations, are balanced, but PC ownership shows a statistically significant difference. The absence of systematic differences between the covariates supports the validity of the design. The limited statistically significant results observed can be attributed to random variation considering the large number of tests performed.

Table 13: Regression Discontinuity Estimates on Covariates (2015)

Variable	τ
Student behavior	
Priority order	-0.034
Deadlines	0.007
Priorities	0.060
Anticipate plans	0.035
Sociodemographic and Scholarships	
Perceived socioeconomic status	-0.117
Mother education	0.148
Father education	0.392*
Academic scholarship	0.047
Income scholarship	0.085
Talent scholarship	0.015
Goods and Services	
# TVs	0.084
# PCs	0.267**
Car (dummy)	-0.024
# Bathrooms	0.129
# Vacations	0.105
Tablet (dummy)	0.167
Land line (dummy)	0.011
Washer (dummy)	0.062
Refrigerator (dummy)	-0.012
Microwave (dummy)	0.023
Internet (dummy)	0.122
Cable TV (dummy)	-0.004

Notes: Estimates are obtained from separate RD specifications using the retakers subpopulation. Each row reports the estimated discontinuity at a seven GPA threshold for the corresponding covariate. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.2 Treatment Effect at Artificial Thresholds

Table 14 reports placebo RD estimates on the probability of retaking the COMIPEMS exam at alternative GPA thresholds not subject to the policy rule. The estimated LATEs are statistically significant at the 7.5 and 9.0 thresholds, but not at 8.0, 8.5, or 9.5. The presence of significant effects at some placebo thresholds suggests that non-policy related factors may influence retake behavior at certain points in the GPA distribution. This pattern warrants a cautious interpretation of the estimated discontinuity at 7.0, as it could partly reflect idiosyncratic variation unrelated to the policy. Further inspection of the distribution of retakers is therefore necessary to determine whether the observed jump at 7.0 reflects such idiosyncratic factors in addition to or instead of the policy effect. This analysis is performed in the next subsection 5.3.

Table 14: Falsifying Test on Probability of Retaking

	RDD				
	7.5	8.0	8.5	9.0	9.5
	(1)	(2)	(3)	(4)	(5)
τ_S	0.015**	0.001	0.007	0.014**	0.005
SE	0.006	0.005	0.005	0.006	0.006
Bandwidth	0.25	0.34	0.43	0.34	0.41
Bias	0.005-0	-0.002-0	0.001-0	0.002-0	0.003-0.001
Obs.	23,995-36,528	35,683-44,645	42,769-44,572	25,353-29,410	27,633-20,573

Notes: This table reports canonical RD design estimates of a linear probability model. Each column presents placebo estimates evaluated at alternative GPA thresholds. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 15 presents the corresponding placebo tests for the COMIPEMS test scores. Across all placebo thresholds, the estimated coefficients are negative, small in magnitude, and statistically insignificant. The absence of positive or significant effects at any non-policy thresholds strengthens the credibility of the main findings, as the significant improvement in test scores at the 7.0 threshold is not mirrored elsewhere in the GPA distribution. In these placebo estimations, it is sufficient to employ the canonical RD design, since no selection is expected at thresholds that are not policy relevant.

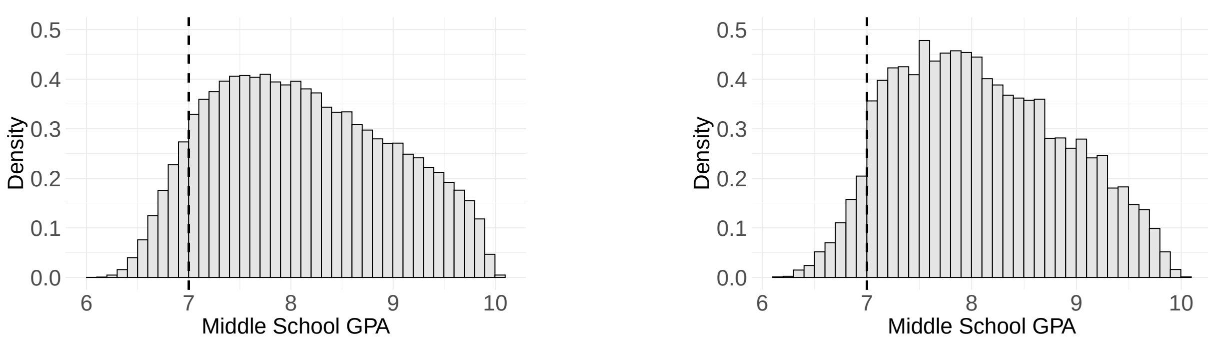
Table 15: Placebo Test Score RDD

	RDD				
	7.5	8.0	8.5	9.0	9.5
	(1)	(2)	(3)	(4)	(5)
τ	-0.027	-0.035	-0.075	-0.062	-0.074
SE	0.066	0.063	0.073	0.073	0.073
Bandwidth	0.41	0.37	0.33	0.34	0.42
Bias	0.009–-0.001	-0.016–0.002	0.001–0.005	0.022–0.002	-0.018–-0.009
Obs.	3,413–4,534	2,654–3,359	2,300–2,702	1,798–2,111	1,929–1,097

Notes: This table reports canonical RD design estimates on test scores. Each column presents placebo estimates evaluated at alternative GPA thresholds. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.3 Continuity

Continuity of the density of the running variable at seven middle school GPA provides credibility against self-selection, it guards against sorting or manipulation, and supports comparability between students above and below the policy. By contrast, a density jump signals sorting at the margin, so any outcome discontinuity cannot be attributed solely to the policy. Establishing discontinuities in the distribution under the current setup is a challenging task for three main reasons. Firstly, the running variable is coarse, as GPA grading occurs at 0.1 intervals, thereby lacking true continuity. Consequently, it is not possible to approximate the densities to the right $f^+(r)$ and left $f^-(r)$ of a cutoff point (r) using standard kernel methods, and discrete support of the running variable can introduce artificial jumps between adjacent GPA values. Secondly, the number of students above and below arbitrary middle school GPAs can display abrupt jumps that reflect grading conventions rather than policy effects. Such discontinuities may arise simply because teachers tend to cluster grades around certain values (ter Meulen, 2023; Bowden et al., 2023) or bunching students at a passing grade (Diamond and Persson, 2016). Thirdly, if discontinuities are already present in the full sample due to institutional conventions or any unrelated policy intervention, observed discontinuities among retakers could potentially reflect pre-existing patterns rather than strategic manipulation.



(a) 2015 First-time Takers

(b) 2016 Restricted Retakers Subsample

Figure 9: Running Variable Densities

Notes: This figure shows histogram of the running variable using 0.1 wide bins. Panel (a) shows the all first-time takers in 2015; Panel (b) show the retakers subpopulation.

To inspect discontinuities around the threshold, I explore the histograms for first-time takers and retakers (Figure 9) using 0.1 wide bins that exactly match the coarseness at which GPA is recorded. For first-time takers, the distribution of the running variable appears smooth, as illustrated in Figure 9a. By contrast, the retaker distribution (Figure 9b) is more jagged and exhibits a substantial jump at the 7.0 GPA threshold. Notwithstanding its limitations in addressing the identified issues, to test whether the running variable distribution exhibits discontinuities, I implement the McCrary (2008) test, that is the standard diagnostic for manipulation in RD design estimations, at $r \in \{7.0, 7.1, 7.2, \ldots, 9.4, 9.5\}$ using a bandwidth of 0.5. To ensure that the reported discontinuities are not spurious, given the coarse 0.1 increments of the running variable, I impose a stricter criterion and report only results that are significant at the 1% level. Table 16 reports the results. For first-time takers, statistically significant discontinuities are found at GPA cutoffs of 7.0, 8.0, 8.3, 8.5, and 9.0. Except for the 8.3 cutoff point, all align with grading values that are attractive focal points for teachers, such as whole numbers or half-point marks, consistent with institutional grading conventions rather than abrupt changes in the underlying student performance. For retakers, the reduced number of observations lowers statistical power. Nonetheless, a discontinuity persists at the 7.0 threshold, while other focal grading values display no observable discontinuities.

Table 16: McCrary Density Test by Cutoff

GPA	**First-time takers**	**Retakers**
7.0	$\star$	$\star$
8.0	$\star$	
8.3	$\star$	
8.5	$\star$	
8.7		$\star$
9.0	$\star$	

Notes: This table reports results from the McCrary (2008) density test at various middle school GPA thresholds. $\star$ denotes significance at the 1% level.

Given the McCrary test results, a remaining concern is that the discontinuities reflect baseline composition differences and not retakers sizable effects in the running variable. To address this, I implement the equivalence testing procedure proposed by Fitzgerald (2025), which evaluates whether any discontinuity is significantly large. Let $f^{+}(r_0)$ and $f^{-}(r_0)$ denote the right and left limits of the density of the running variable at the policy threshold r_0, and define the right-to-left ratio $\rho(r_0) = f^{+}(r_0)/f^{-}(r_0)$ with $\theta = \log \rho(r_0)$. The test constructs an equivalence confidence interval (ECI) for $\hat{\theta}$ from the data, and compares it with a researcher chosen ratio $\varepsilon = f^{+}(r_0)/f^{-}(r_0) > 1$. In the absence of specific data regarding the anticipated magnitude of the discontinuity (information about ε). I report the upper and lower ECI bounds.

Figure 10 displays the Fitzgerald ECI across GPAs, evaluated at the 5% significance level. From 7.0 to 8.0, I display the upper bound ratio consistent with the maximum upward jump admissible in the density. From 8.1 onward, I plot the lower bound consistent with the maximum admissible drop. The procedure is symmetric. For instance, a right-to-left density ratio of 2 is equivalent to a 100% upward jump, whereas a ratio of 1/2 is equivalent to a 50% downward drop. At $r_0 = 7.0$, the retaker sample yields a maximum ratio of 1.85, which implies a maximum jump of 85%. In contrast, for first-time participants at the same GPA, the maximum jump is calculated at 1.10, a 10% jump. ECIs provide a framework for comparing a given ε across the distributions of first-attempt takers and retakers at different GPAs. For example, a discontinuity in the running variable corresponding to a tolerance ratio of $\varepsilon = 1.5$ is rejected as equivalent only at a GPA of seven for retakers.[26] For other GPA values, the same tolerance level would not reject equivalence, implying that any differences are sufficiently small to be considered negligible. The ECI offers reassurance that the jump observed at seven GPA is sufficiently large for the selection approach to be well grounded.

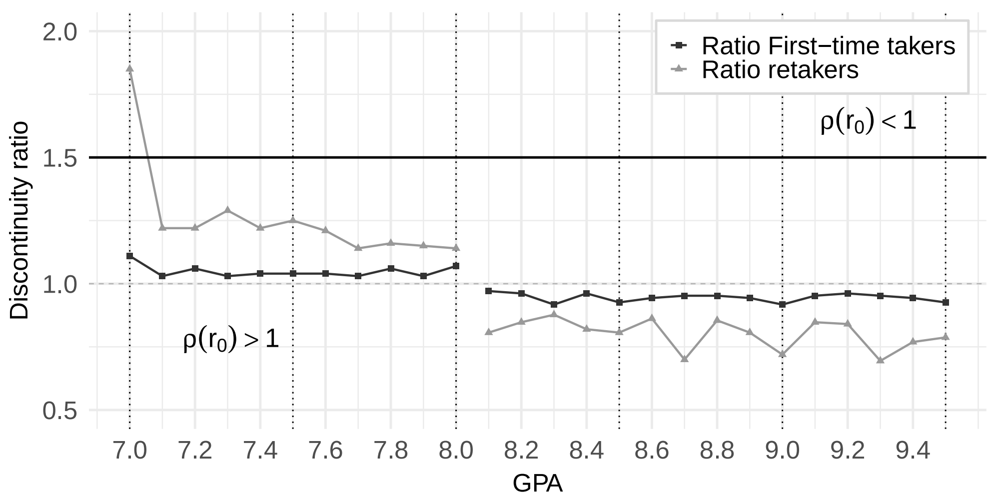


Figure 10: Fitzgerald Bounds

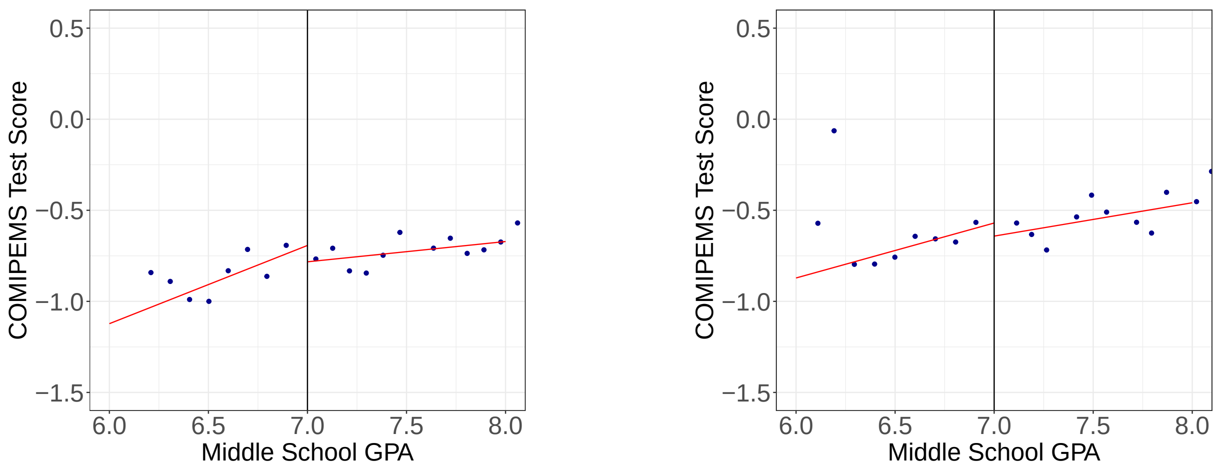
Note: This figure plots Fitzgerald equivalence confidence intervals (ECIs) at the 5% level at different GPA thresholds. For GPA thresholds between 7.0 and 8.0, ratios greater than one indicate upward discontinuities, whereas for thresholds above 8.0, ratios below one indicate downward discontinuities (drops). The solid line corresponds to the researcher chosen ratio $\varepsilon = 1.5$.

5.4 Students not interested in Elite Schools

A discontinuity at a GPA of 7.0 among students who did not express interest in elite schools would indicate that forces other than elite school aspirations contribute to the observed

[26]The choice of the tolerance ratio, ε, is inherently arbitrary. In this context, setting $\varepsilon = 1.5$ provides a credible benchmark, as it exceeds the observed density jump of roughly 30%.

jump in COMIPEMS test scores. Figure 11 provides no indication of such a discontinuity for students not interested in elite schools, and this evidence is supported by Table 17, which presents estimation results that reveal no significant effects for years 2015 and 2016 on both the standard and the donut estimates. The absence of discontinuity is attributed to their indifference toward the high stakes associated with elite educational pathways. Thus, the academic performance of these students reflects a steady and consistent level of effort that does not change significantly as a result of approaching policy middle school GPA.



(a) 2015

(b) 2016

Figure 11: Regression Discontinuity on Test Scores for Students not Interested in Elite Schools

Notes: This figure displays the results from first-order local polynomial regressions on students no interested in pursuing elite schools, with middle school GPA on the horizontal axis and normalized COMIPEMS entrance exam scores on the vertical axis. Panel (a) includes the all retakers in 2015, while Panel (b) show the results for the all retakers in 2016.

6 Families' Financial Investment

The COMIPEMS survey provides information about how students prepare for the exam, asking them if they took courses at their school, at a private institution, or with a tutor. The responses are recorded as dichotomous variables, coded one if the respondents engage in any form of preparation, and zero otherwise. Among retakers in 2016, 33.0% reported taking courses at their school, 32.2% enrolled in courses offered by private institutions, and 17.8% received support from a private tutor during their first application attempt. To assess whether eligibility for elite schools affected these preparation choices, I estimate a linear probability model using a RD design framework at the policy GPA threshold.

Table 17: LATE on COMIPEMS Scores
(Students not Interested in Elite Schools)

	RDD 2015		RDD 2016	
	(1) Standard	(2) Donut	(3) Standard	(4) Donut
Coefficient	-0.135	0.081	-0.092	0.085
SE	0.14	0.182	0.134	0.183
Bandwidth	0.37	0.32	0.39	0.33
Bias	-0.053 – -0.007	-0.025 – -0.124	-0.061 – -0.011	-0.038 – -0.128
Effective obs.	296 – 409	296 – 306	373 – 432	373 – 321

Notes: This table reports canonical RD design estimates on test scores for students not interested in attending elite schools. Donut specifications exclude observations with a 7.0 middle school GPA. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 18 presents the estimation results. For 2015, the share of students taking courses at their schools, at private institutions, or with a private tutor does not differ between those eligible for elite institutions and those who are not. This is consistent with students not being aware of their middle school GPA. In contrast, in 2016, students who were not eligible to attend elite schools were 15.1 pp more likely to take courses at their schools, compared to eligible students, while students who were eligible to attend elite schools were 14.4 pp more likely to take courses at private institutions. Given that courses offered by students' schools are generally free, the fact that eligible students are more likely to enroll in private preparatory institutions indicates that elite school eligibility leads families to invest additional financial resources in exam preparation compared to otherwise similar ineligible students. When accounting for the cost of private preparatory courses as a proportion of monthly expenditure (Table 3), the results suggest that families devote substantial financial resources to securing elite school admission. [27]

[27] The robustness of the RD design is confirmed across specifications employing differences, lags, and controlling for unobservable characteristics. Additional details and supporting results are provided in Appendix A6.

Table 18: LATE on the Probability of Taking Courses

	RDD 2015		RDD 2016	
	Standard	Donut	Standard	Donut
	(1)	(2)	(3)	(4)
in school	-0.058	-0.048	-0.151***	-0.097*
	(0.066)	(0.074)	(0.058)	(0.055)
in private institution	0.082	0.086	0.144**	0.135*
	(0.065)	(0.074)	(0.070)	(0.079)
private tutor	0.012	-0.011	-0.022	-0.012
	(0.055)	(0.062)	(0.060)	(0.068)

Notes: This table reports canonical RD design estimates of a linear probability model on the probability of taking courses in school, at a private institution, or with a private tutor for the high school entrance exam. Donut specifications exclude observations with a 7.0 middle school GPA. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

7 Conclusion

This study offers quantitative assessment of the perceived value of elite schooling by measuring the additional effort students exert when retaking the high school entrance exam. Exploiting a policy rule that deems students with a middle school GPA below 7.0 ineligible for admission to elite schools, I estimate the additional effort in question by comparing performance on exam retaking between students just above and below the eligibility threshold. The results show that the eligibility to gain access to an elite school motivates additional effort: the preferred estimate indicates a 0.10 standard deviation increase in test scores, equivalent to a 5 percentage point higher probability of admission to an elite institution. There is also evidence of self-selection into retaking the exam, as well as greater financial investment by the families of eligible students, who are more likely to enroll in costly private preparatory courses, while ineligible students rely primarily on free school-based options.

A limitation of this study is that the estimates identify LATE rather than the average treatment effect (ATE). Thus, the estimates capture the effort of students at the eligibility margin and may not be generalized to the broader population of applicants. Nonetheless, it is reassuring that the results remain statistically significant even when identified at the lower end of the GPA distribution. Although the institutional setting is specific to Mexico City, the underlying mechanism is relevant to many other countries where high-stakes entrance exams determine admission to selective schools and universities. In such contexts, the effort response is likely to be even more pronounced, as students and their families face intense pressure to secure access to elite institutions.

The connection between effort on admission exam and elite school eligibility is relevant in the context of centralized school matching mechanisms, where exam performance determines access to selective schools but the role of student effort remains largely unobserved. To the best of my knowledge, few studies explicitly incorporate effort into the student decision-making process (e.g., Arslan, 2022) and none characterize it quantitatively, suggesting a promising avenue for future research. Extending this framework to dynamic models of student preparation and application choices would further illuminate how expectations, competition, and constraints jointly shape educational outcomes in selective admission systems.

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A1 Share of Students Listing at Least One Elite School

Table A1: Share of Students Listing at Least One Elite School (All Students, 2015)

	First Attempt (2015)		
GPA	**First**	**Top 5**	**All**
6.5	0.38	0.45	0.51
6.6	0.42	0.50	0.55
6.7	0.46	0.53	0.59
6.8	0.48	0.55	0.61
6.9	0.51	0.59	0.64
7.0	0.58	0.68	0.74
7.1	0.58	0.67	0.73
7.2	0.60	0.68	0.73
7.3	0.60	0.69	0.75
7.4	0.61	0.69	0.74
7.5	0.62	0.69	0.74
7.6	0.62	0.69	0.74
7.7	0.62	0.70	0.75
7.8	0.64	0.72	0.76
7.9	0.64	0.71	0.76
8.0	0.65	0.73	0.77

Note: This table shows the share of students who ranked at least one elite school in their ROL, either as their first choice, within the top five, or anywhere in the list.

A2 Policy

Figure 12 illustrates the effects of the policy in the 2016 COMIPEMS matching using histograms of COMIPEMS test scores for four groups, formed by the interaction of elite and non-elite schools and first-time takers and retakers. The vertical line in Figure 12 shows the minimum test score required for a student to gain admission to an elite high school. Students with test scores to the right of the line meet the admission requirement. Exclusively students with a GPA of seven or higher are matched with elite schools (left histograms). Conversely, all students with GPAs below seven are matched with non-elite schools (right histograms).

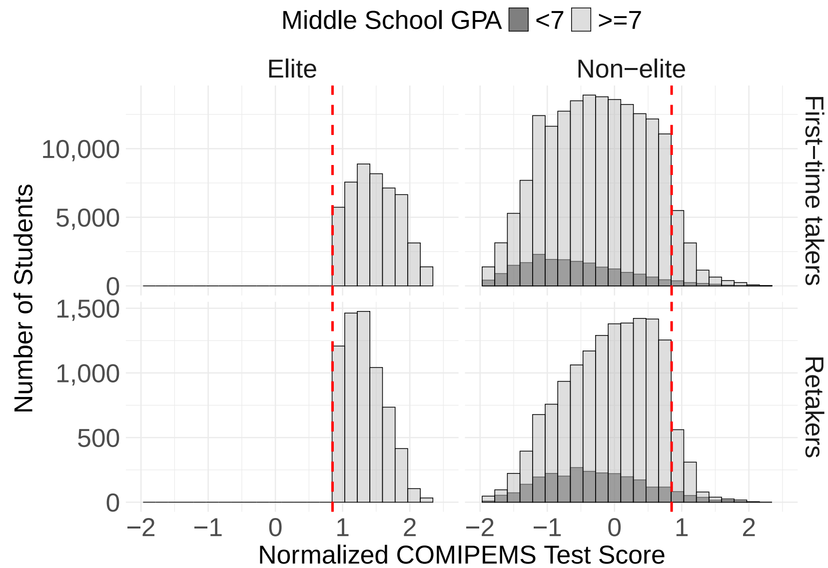

Figure 12: Sharp Policy Cutoff

Notes: This figure shows histograms of normalized COMIPEMS test scores in 2016 for four groups (elite vs. non-elite × first-time takers vs. retakers). The vertical line in the left panel is positioned at the minimum score required for elite admission.

A3 GPA Sensitivity at the End of Middle School

In the Mexican secondary school system, students typically take nine courses each year, and their final GPA is based on a series of bimonthly grades recorded throughout the three years of middle school. At the end of the third year, the students accumulate more than 100 grades, each contributing to the final GPA. As the academic year draws to a conclusion, most of the grades are already fixed, leaving students with limited room to influence their final GPA. For students near the eligibility threshold, the need to attain a 7.0 GPA generates a high-stakes environment in which they may attempt to secure a 7.0 GPA through additional effort, strategic behavior, or even attempts to influence grading practices.

The implementation of SIGED in 2013 (Sistema de Información y Gestión Educativa), which standardized the process by which grades are reported and recorded in public schools in Mexico, limits the students' opportunity to rig the system. In this digital platform, teachers submit grades directly into an online system, reducing opportunities for informal grade negotiation after the official grading period closes. In the last two-month period, often the last opportunity to improve, students can still try to influence their results. However, achieving even a small change in the final GPA would require consistently high scores in multiple subjects. In practice, if a student is unable to achieve higher grades through academic performance alone, this may imply the need to appeal to multiple teachers for more favorable assessments. A back of the envelope calculation indicates that a student with a prior GPA of 6.9 would need to convince at least four teachers to award perfect scores of 10 in the final grading period in order to reach a 7.0 GPA, or alternatively persuade all nine teachers to grant just one additional point above their current performance of 6.9.

A4 Gains Density

To characterize how student improvements are distributed, I plot kernel density estimates of the gain in COMIPEMS test scores, defined as the retake score minus the first-take score, separately for students eligible for elite schools and for ineligible students. Results are similar under alternative kernels and bandwidth choices. The eligible density lies to the right and places more mass in the upper tail, which indicates larger improvements on average and across much of the distribution.

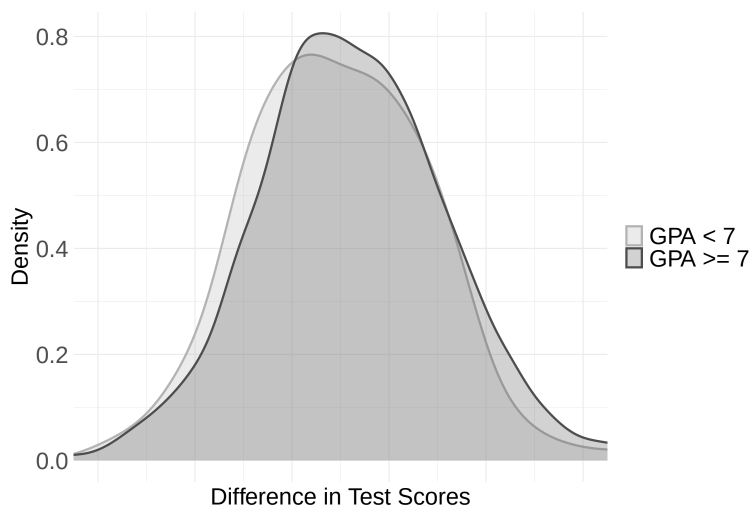

Figure 13: Density of Test Score Differences by Elite Eligibility

Notes: This figure presents kernel density estimates of test score differences by eligibility status for elite high schools.

A5 Null Treatment Effect on Predetermined Covariates

One of the key identification assumptions in RD designs is that there are no discontinuous jumps in predetermined covariates at the cutoff. This appendix provides visual evidence that the distribution of covariates is smooth around the middle school policy threshold.

Students Behavior

The COMIPEMS questionnaire assesses student behaviors related to establishing priorities, priorities order, deadlines, and anticipating important activities. Students responded in a discrete scale from one to four, where one indicated the behavior was seldom exhibited and four indicated it occurred almost all the time. Learning about these behaviors provides valuable insight into students time management and planning skills, which are key factors in maintaining consistent academic progress and achieving long-term educational goals. The visual inspection of Figure 14 shows no indication of discontinuities in student behavior, suggesting that these covariates are balanced at the middle school threshold.

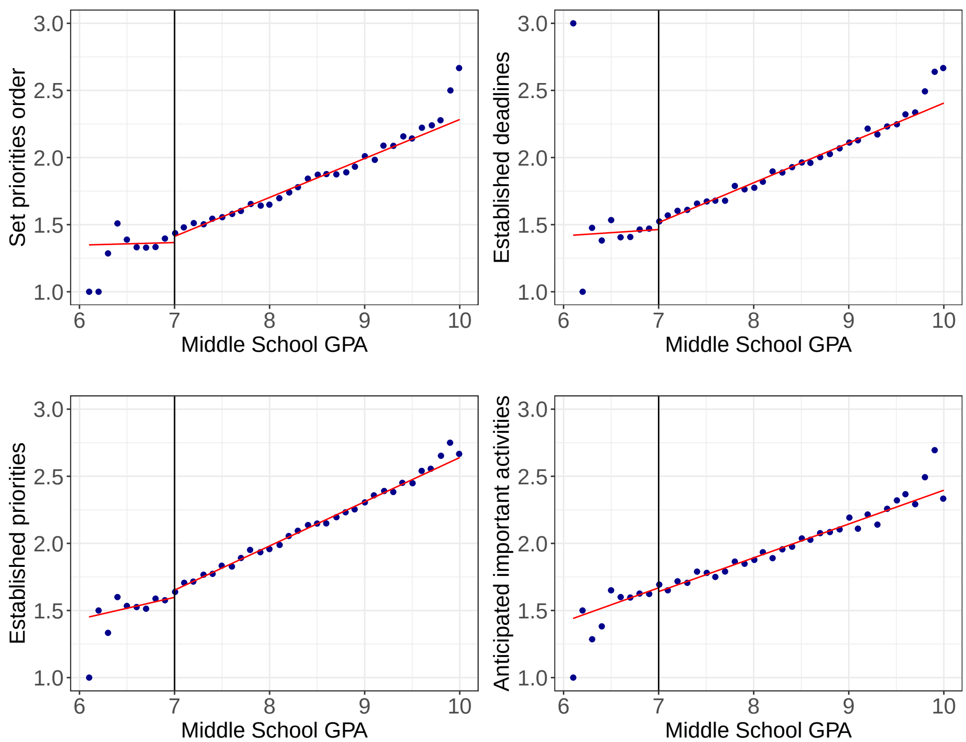

Figure 14: Covariates on students' behavior (2015)

Note: This figure displays results from first-order local polynomial regressions, using survey responses as outcome variables.

Sociodemographic and Scholarship

The registration form collects information about students' perceived socioeconomic status, parental education, and receipt of middle-school scholarships. These factors are important determinants of educational outcomes. Perceived socioeconomic status shapes students' confidence, aspirations, and access to resources, which often influence academic performance.

Parental education provides important foundations, as parents with higher education tend to offer more academic support and set higher expectations for their children's success. Mother's education, in particular, is often associated with early cognitive development and school readiness. Scholarships, whether for academic merit, financial need, or sports, help alleviate financial pressures and provide incentives for academic improvement. A visual inspection of the aforementioned variables in Figure 15 reveals no apparent discontinuities.

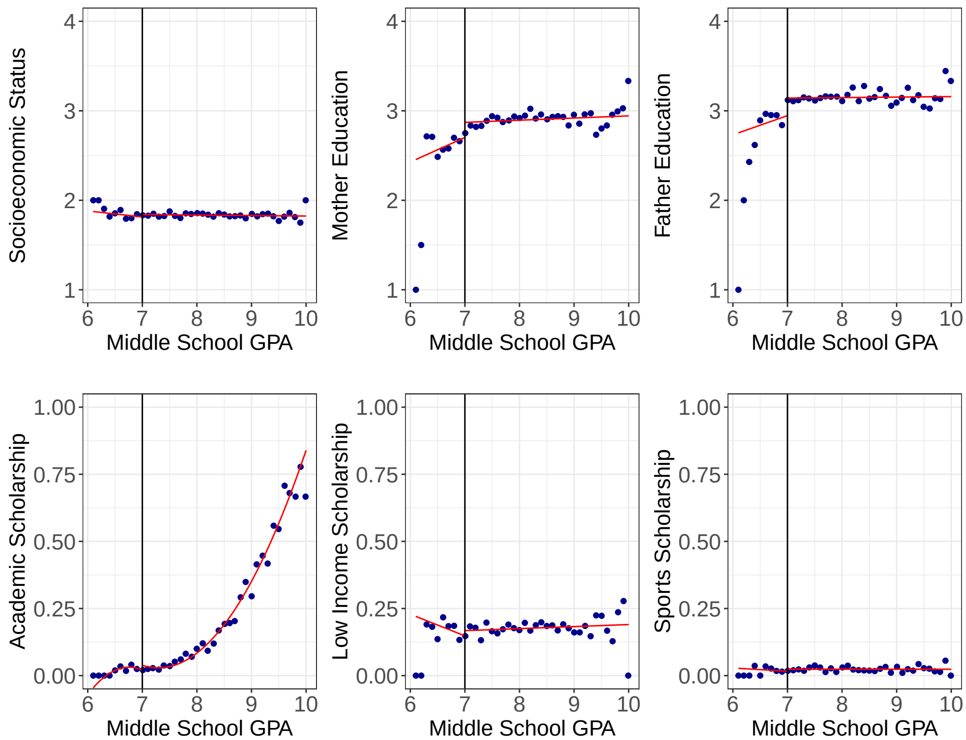

Figure 15: Sociodemographic and Scholarship Covariates (2015)

Notes: This figure displays results from first-order local polynomial regressions, using survey responses as outcome variables.

Good and Services

Goods and services such as the number of TVs, PCs, cars, bathrooms, annual vacations, tablets, landlines, washing machines, and other household items are not directly linked to educational performance, as these items themselves do not inherently affect a student's ability to learn or succeed academically. However, they can serve as indicators of socioeconomic status, which is often closely tied to educational outcomes. Higher access to such goods and services generally reflects a household's greater financial stability, access to resources, and overall living conditions. Families with better socioeconomic standing are more likely to provide supportive environments for learning, access to educational materials, and opportunities such as extracurricular activities, tutoring, or better schooling options. The visual inspection of Figure 16 shows no clear discontinuities in the distribution of goods and services, indicating that there are no differences in the access to these items between students just above and below the threshold.

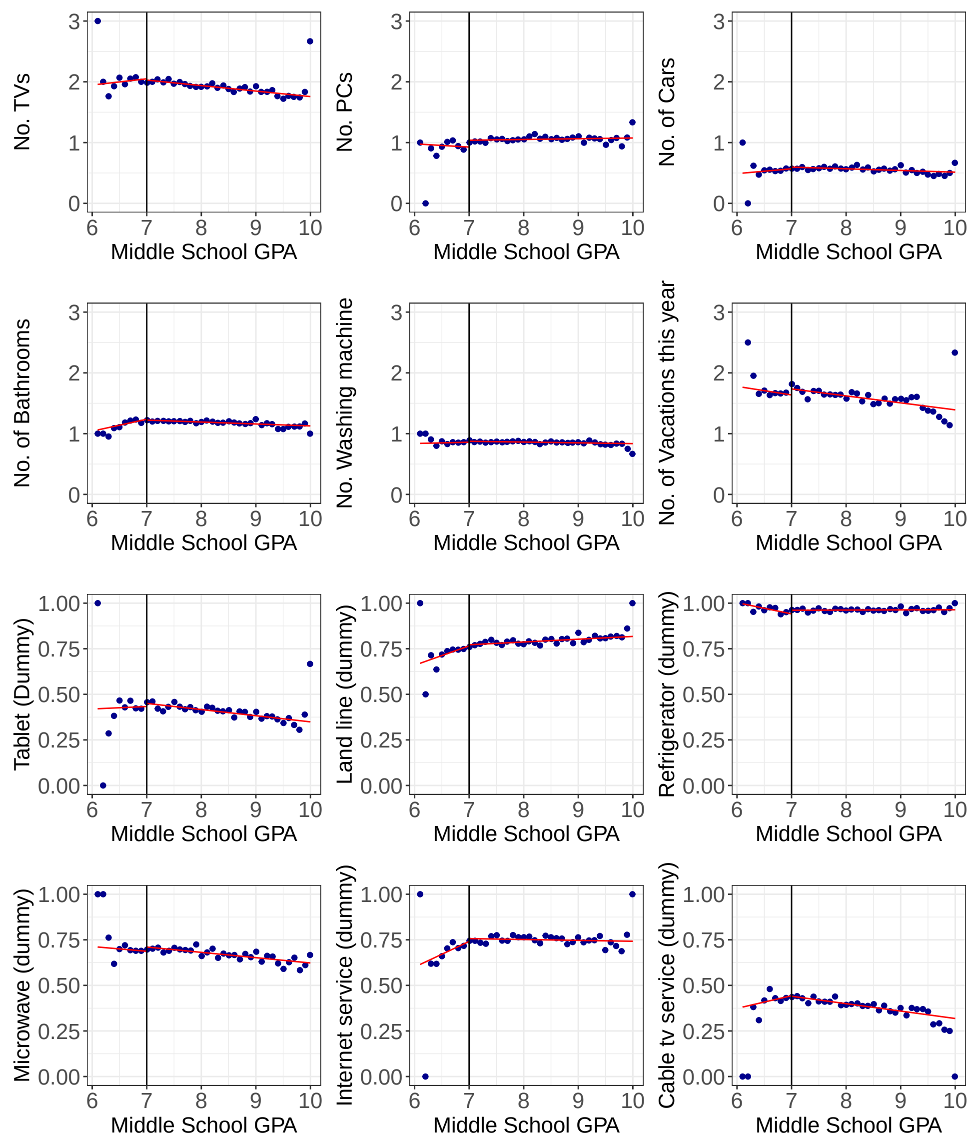

Figure 16: Covariates on goods and services (2015)

Notes: This figure displays results from first-order local polynomial regressions, using survey responses as outcome variables.

A6 LATE on Probability of Taking Courses

Table A2: LATE on the Probability of Taking Courses
(difference and lag)

	diff		lag	
	Standard	Donut	Standard	Donut
	(1)	(2)	(3)	(4)
in school	-0.118	-0.058	-0.150***	-0.095*
	(0.093)	(0.092)	(0.058)	(0.055)
in private institution	0.063	0.004	0.128*	0.111
	(0.091)	(0.099)	(0.070)	(0.078)
private tutor	0.048	0.050	0.006	0.004
	(0.092)	(0.091)	(0.070)	(0.069)

Notes: This table reports RD design estimates of a linear probability model on the probability of taking courses in school, at a private institution, or with a private tutor for the high school entrance exam for two alternatives specifications. In the difference specification, the outcome variable is the difference in test scores. In the lag specification, the outcome variable is the 2016 test score, and the lagged test score is included as a covariate. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A3: LATE on the Probability of Taking Courses
(controlling for unobservables)

	RDD 2015		RDD 2016	
	Standard	Donut	Standard	Donut
	(1)	(2)	(3)	(4)
in school	-0.026	0.008	-0.148***	-0.098
	(0.078)	(0.089)	(0.055)	(0.062)
in private institution	0.051	0.097	0.122*	0.106
	(0.077)	(0.089)	(0.068)	(0.090)
private tutor	-0.030	-0.073	-0.011	0.025
	(0.065)	(0.075)	(0.069)	(0.079)

Notes: This table reports RD design estimates of a linear probability model on the probability of taking courses in school, at a private institution, or with a private tutor, controlling for the proportion of elite schools in students' ROL. Donut specifications exclude observations with a 7.0 middle school GPA.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A4: Intensive Margin Estimates on the Probability of Taking Courses

	in school		in private institution		private tutor	
	standard	donut	standard	donut	standard	donut
Intesive Margin	-0.151	-0.097	0.144	0.135	-0.022	-0.012
bounds	[-0.61, 0.25]	[-0.52, 0.28]	[-0.42, 0.67]	[-0.47, 0.66]	[-0.55, 0.49]	[-0.58, 0.50]

Notes: The table shows the intensive margin estimates of a linear probability model on the probability of taking courses in school, at a private institution, or with a private tutor, and the corresponding bounds under monotonic selection.

Acronyms

School Systems

COLBACH Colegio de Bachilleres

CONALEP Colegio Nacional de Educación Profesional Técnica

DGB Dirección General del Bachillerato

DGETAyCM Dirección General de Educación Tecnológica Agropecuaria y Ciencias del Mar

DGETI Dirección General de Educación Tecnológica Industrial y de Servicios

IPN Instituto Politécnico Nacional

SE Secretaría de Educación del Gobierno del Estado de México

UAEM Universidad Autónoma del Estado de México

UNAM Universidad Nacional Autónoma de México

Government Agencies

COMIPEMS Commission of Public Institutions of Upper Secondary Education

INEA National Institute for Adult Education

INEGI National Institute of Statistics and Geography

PROFECO Federal Consumer Protection Office

Abbreviations

DLP distance to least-preferred elite school

ROL rank order list