Flourish or Fail?: The Risky Reward of Elite High School Admission in Mexico City

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ABSTRACT

Admission to an elite school imposes substantial risks on many students while offering modest academic benefits relative to admission in their most preferred nonelite school. Using variation in school assignment generated by the allocation mechanism, we find that admission to a system of elite public high schools in Mexico City increases the probability of high school dropout by 9.4 percentage points. Students with weaker middle school grades and whose commutes are lengthened by elite admission experience a larger rise in dropout probability. On the other hand, elite admission raises end-of-high-school math test scores for the marginal admittee, even when accounting for potential bias due to admission-induced dropout.

I. Introduction

Families often have some choice in where their children attend school, and all else equal, most families prefer a school of higher academic quality (see, for example, Hastings, Kane, and Staiger 2009). Attending a "better" school, as defined by peer ability or school resources, is usually thought to benefit students academically. For example, a student may benefit from working with high-achieving and highly motivated peers, and a better-funded school is able to afford more and better educational inputs.

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But there is also a risk to attending a better school, particularly if doing so means that the student is closer to the bottom of the school-specific ability distribution. The difficulty level of the coursework may prove too much for the student to handle. Teachers may teach mostly to the top of the class, leaving behind those who enter the school with a weaker academic background. An additional difficulty arises when students must commute farther to attend a better school instead of a nearby neighborhood school. Students experiencing such challenges may fail to complete their education at all, which is probably a much less desirable outcome than graduating from a lower-quality school.

This paper quantifies the tradeoff between academic benefit and dropout risk facing students admitted to a subset of Mexico City's elite public high schools. Mexico City is ideal for this exercise for three reasons. First, there are large perceived disparities in public high school quality, with a well-identified group of "elite" schools standing above all others. This gives a natural definition of what an "elite" (or "better") school is. Second, nearly all public high schools in the city participate in a unified merit-based admissions system, using a standardized exam and students' stated preferences to allocate all students across schools. This mechanism allows us to credibly identify the impact of elite school admission on dropout probability and end-of-high-school exam scores. Third, Mexico is characterized both by a high secondary school dropout rate and a significant estimated economic return to high school education, so the risk of dropping out is a first-order issue facing students. In our sample, about half of students who are assigned to a high school do not take the end of high school standardized exam three years later.[1] At the same time, young men with a high school diploma have 24 percent higher wages than those who only completed middle school (Campos-Vazquez 2013). Although this is not a causal relationship, and there may be some value in attending an elite school even if the end result is dropping out, this wage differential is suggestive that dropping out has a real cost for students.

A regression discontinuity design, made possible by the assignment mechanism, is used to discover whether students experience a change in dropout probability and in end-of-high-school exam scores as a result of admission to an elite school, using their most-preferred nonelite school that would admit them as the counterfactual. We find that there is a clear tradeoff for most marginally admitted students. Admission to an elite school raises their probability of high school dropout by 9.4 percentage points, compared to an average probability of 42 percent among marginally rejected students. Along with this substantial increase in dropout probability, elite school admission also results (on average) in gains on the math portion of the 12th grade standardized exam. Estimated effects on the Spanish section of the exam are positive but statistically insignificant. Because elite admission increases the probability of dropout and thus decreases the probability that admitted students take the standardized exam, the estimated exam score effects are likely to be biased. In particular, if elite schools fail out their worst

1. Mexico's Report on the National Survey of High School Dropout provides extensive insight into the patterns and correlates of dropout at the national level (Martínez Espinosa et al. 2012). Most dropout appears to be initiated by the student rather than the school, as only 13.9 percent of dropouts mention being dropped for failing too many classes or being expelled for disciplinary reasons as a principal factor in their decision to leave high school.

students, then positive test score effects could reflect the composition of test-takers rather than academic gains. In order to provide bounds for the exam score effects in the presence of such bias, we apply Lee's (2009) bounding method to the regression discontinuity setting. The resulting lower bound of the effect of elite admission on math scores is 0.12 standard deviations, an effect that applies to the population of students who eventually graduate from high school whether or not they are assigned to an elite school.

Students with lower middle school grade point averages experience larger increases in dropout probability, but there is no evidence that they experience a smaller boost in their exam scores from elite admission. Beyond the pressure exerted on lower-achieving students, elite admission increases the opportunity cost of school attendance by substantially increasing commuting distance to school. Mexico City is geographically very large and many students travel far to attend high school: The mean one-way (straight-line) commuting distance is 7.1 km, while 10 percent of students travel 15.3 km or more each way. On average, marginally admitted elite school students are assigned to schools 4.5 km farther away than their most-preferred alternative. Marginal admission to an elite school increases dropout probability more when admission results in a longer commute. The problem of travel distance for elite schools is not unique to Mexico City. For example, Abdulkadiroglu, Angrist, and Pathak (2014) find that students in New York City and Boston must travel farther to attend elite "exam high schools" than to their next-best option. We note, however, that commuting distance is but one factor affecting dropout risk—in our case, elite admission increases the probability of dropout even for students whose commute decreases due to admission.

Most previous studies on the effects of elite high school admission have focused on the impact on exam scores. Such studies typically analyze cases of merit-based admission systems, and use a sharp or fuzzy regression discontinuity design to estimate the effect of elite school admission on outcomes. Most have found zero or modest effects: Clark (2010) in the United Kingdom, Abdulkadiroglu et al. (2014) in Boston and New York, Lucas and Mbiti (2014) in Kenya, and Ajayi (2014) in Ghana all find zero or negligible impacts from elite high schools while Jackson (2010) and Pop-Eleches and Urquiola (2013) find a modest benefit of admission to high schools with higher-scoring peers in Trinidad and Tobago and Romania, respectively. Zhang (2012) exploits a randomized lottery for elite Chinese middle schools to show that elite admission has no significant impact on academic outcomes. Beyond the zero effect on exam scores, Dobbie and Fryer (2014) find that the New York elite high schools do not have an appreciable effect on long-run outcomes such as SAT score or college graduation. Estrada and Gignoux (2015) use a similar empirical strategy to ours with one year of COMIPEMS data and a separate survey (administered in a subsample of high schools) to estimate the effect of elite school admission on subjective expectations of the returns to higher education, finding that admission leads to higher expected returns. We will expand further on the relationship between their work and the present paper.

In a much different study, Duflo, Dupas, and Kremer (2011) randomly assigned Kenyan schools into a tracking regime where they divided their first grade classes by student ability. They find that while tracking is beneficial, there is no evidence that being in a class with better peers is the mechanism through which these benefits are manifested. We note that in the case of admission to competitive elite schools, admission results both in a more able peer group as well as a different schooling environment with resources, management, and culture that might be quite different from other public schools. Thus the effect of elite school admission is a reflection of both the peer and institutional channels, which regression discontinuity designs such as the present one cannot effectively disentangle.[2]

The literature on the relationship between school quality and student dropout is sparser. Recent studies mostly have focused on the impacts of specific aspects of quality, randomly varying one aspect to see if it increased school attendance, which differs from the concept of dropout in that reduced attendance may not result in permanently abandoning schooling while dropout usually does. For example, Glewwe, Ilias, and Kremer (2010) find no effect of a teacher incentive pay scheme on student attendance in Kenyan public primary schools. More related to our study, de Hoop (2011) estimates the impact of admission to competitive, elite public secondary schools on dropout in Malawi. He finds that admission to such schools decreases dropout. This could be due to increased expected returns from an elite education inducing students to attend or because the elite schools provide a more supportive environment. Our findings provide a stark contrast to these results, although in a much different economic and social context.

The rest of the paper is organized as follows. Section II gives a detailed overview of the Mexico City high school admissions system. Section III sets forth the method for identifying the effects of admission on outcomes. Section IV describes the data, and Section V gives the empirical results. Section VI concludes.

II. Mexico City Public High School System and Student Enrollment Mechanism

We first present the institutional environment in which Mexico City's students choose high schools, followed by background information on the elite schools and an explanation of how they differ from other available schooling options.

A. School Choice in Mexico City

Beginning in 1996, the nine public high school subsystems in Mexico's Federal District and various municipalities in the State of Mexico adopted a competitive admissions process. This consortium of schools is known as the Comisión Metropolitana de Instituciones Públicas de Educación Media Superior (COMIPEMS). COMIPEMS was formed in response to the inefficient high school enrollment process at the time, in which students attempted to enroll in several schools simultaneously and then withdrew from all but the most-preferred school that had accepted them. The goal of COMIPEMS was to create a unified high school admissions system for all public high schools in the

2. Further studies on the impact of specific aspects of school quality on test scores include Dearden, Ferri, and Meghir (2002), Newhouse and Beegle (2006), Gould, Lavy, and Paserman (2004), Hastings, Kane, and Staiger (2006), Hastings and Weinstein (2008), Cullen, Jacob, and Levitt (2005 and 2006), and Lai, de Janvry, and Sadoulet (2011).

Mexico City metropolitan area that addressed such inefficiencies and increased transparency in student admissions.

Any student wishing to enroll in a public high school in the Mexico City metropolitan area must participate in the COMIPEMS admissions process. In February of the student's final year of middle school (grade nine), informational materials are distributed to students explaining the rules of the admissions system and registration begins. As part of this process, students turn in a ranked list of up to 20 high schools that they want to attend.[3] In June of that year, after all lists of preferred schools have been submitted, registered students take a comprehensive achievement examination. The exam has 128 multiple-choice questions worth one point each, covering a wide range of subject matter corresponding to the public school curriculum (Spanish, mathematics, and social and natural sciences) as well as mathematical and verbal aptitude sections that do not correspond directly to the curriculum.

After the scoring process, assignment of students to schools is carried out in July by the National Center of Evaluation for Higher Education (CENEVAL), under the observation of representatives from each school subsystem and independent auditors. The assignment process follows the serial dictatorship mechanism (see Abdulkadiroglu and Sonmez 2003) and proceeds as follows.[4] First, each school subsystem sets the maximum number of students that it will accept at each high school. Then, students are ordered by their exam scores from highest to lowest. Any student who scored below 31 points or failed to complete middle school is disqualified from participating.[5] Next, a computer program proceeds in descending order through the list of students, assigning each student to the highest-ranked school with seats remaining when the student's turn arrives.[6] If by the time a student's turn arrives, all of the selected schools are full, the student must wait until after the selection process is complete and choose from the schools with open slots remaining. This stage of the allocation takes place over several days, as unassigned students with the highest scores choose from available schools on the first day and the lowest scorers choose on the final days.

In April of the final year of high school (grade 12), students who are currently enrolled and are expected to graduate in June take a national examination called the Evaluación Nacional de Logro Académico en Centros Escolares (ENLACE), which tests students in

3. Students actually rank programs, not schools. For example, one technical high school may offer multiple career track programs. A student may choose multiple programs at the same school. For simplicity we will use the term "school" to refer to a program throughout. No elite school has multiple programs at the same school, so this distinction is unimportant for the empirical analysis.
4. The serial dictatorship mechanism is a special case of the common student-proposing deferred acceptance (DA) mechanism. DA mechanisms are strategy-proof, provided that students do not face a binding constraint on the number of schools that they can list. In practice, only 2 percent of students exhaust their 20 choices.
5. This restriction was removed in 2013, after the period studied in this paper.
6. In some cases, multiple students with the same score have requested the final seats available in a particular school, so that the number of students outnumbers the number of seats. When this happens, the representatives in attendance from the respective school subsystem must choose to either admit all of the tied applicants, slightly exceeding the initial quota, or reject all of them, taking slightly fewer students than the quota. The number of offered seats and the decisions regarding tied applicants are the only means by which administrators determine student assignment to schools; otherwise, assignment is entirely a function of the students' reported preferences and their scores. Neither seat quotas nor tie-breaking decisions offer a powerful avenue for strategically shaping a school's student body.

Spanish and mathematics.[7] This examination has no bearing on graduation or university admissions, and the results have no fiscal or other consequence for high schools. The exam is given at the student's school, during the regular school day, but is administered by outside proctors. It is a benchmark of student and school achievement and progress.[8]

B. Elite Subsystems

There are two elite high school subsystems in Mexico City, each affiliated with a prestigious national university. The Instituto Politécnico Nacional (IPN) is a university located in Mexico City that focuses on the sciences and engineering. It has 16 affiliated high schools in the city, also known for providing a rigorous education in math and science. This is the elite subsystem on which we will focus, for reasons that will be explained below. The other elite subsystem is affiliated with the Universidad Nacional Autónoma de México (UNAM) and consists of 14 high school campuses. These schools do not stress quantitative coursework like the IPN, but rather offer a broader curriculum. There is an overwhelming public belief that the IPN and UNAM high schools are superior to the rest. For example, following the 2011 assignment process, the major newspaper El Universal ran a story headlined "119 thousand students left out of the UNAM; Only 21 thousand middle school graduates win a spot at the IPN" (2011).[9]

The seven nonelite subsystems offer a range of educational options in their 265 campuses.[10] Some have traditional academic curricula, while others offer technical and vocational training. During the period of study, most technical and vocational schools required that students choose a track offered at the campus, so students actually faced 604 nonelite school-track choices. Figure 1 is a map of the available schools in the COMIPEMS zone, which consists of the Federal District and surrounding municipalities of the State of Mexico. Although all but two of the elite schools are located in the Federal District, several of the UNAM schools and most of the IPN schools are located close to the State of Mexico and are within commuting distance of many students residing there.[11]

7. The ENLACE was discontinued after the 2014 round, to be replaced by another exam in 2015.

8. Our conversations with officials at the Secretariat of Public Education give us the impression that, in its initial years, schools did not prioritize preparation for the ENLACE. Results were disseminated in a way that did not facilitate easy comparisons between schools: Only the school-level percentages of students falling into four categories of competency were reported, and these could only be accessed through the Secretariat's web portal. One had to either enter the school identifier (a code not provided in COMIPEMS application materials) to see the report or download a raw data file containing results for all schools in the country. Value-added measures were not estimated or published. To address the issue of differential preparation empirically, note that the 2008 round of the ENLACE was the first in which the exam was given and that school directors and teachers had very minimal understanding of the kinds of questions their students would encounter. Despite this limitation on the ability of schools to prepare their students, in Appendix Table A1 we see strong effects of admission on math scores and dropout when restricting to the 2005 COMIPEMS cohort, most of whom took the ENLACE in 2008.

9. The original title is "Fuera de la UNAM, 119 mil jóvenes; Sólo 21 mil egresados de la secundaria logran lugar en IPN."

10. This discussion refers to the number of available schools in 2005. There have been minor changes since then.

11. Indeed, 43 percent of students assigned to IPN schools in our sample reside in the State of Mexico.

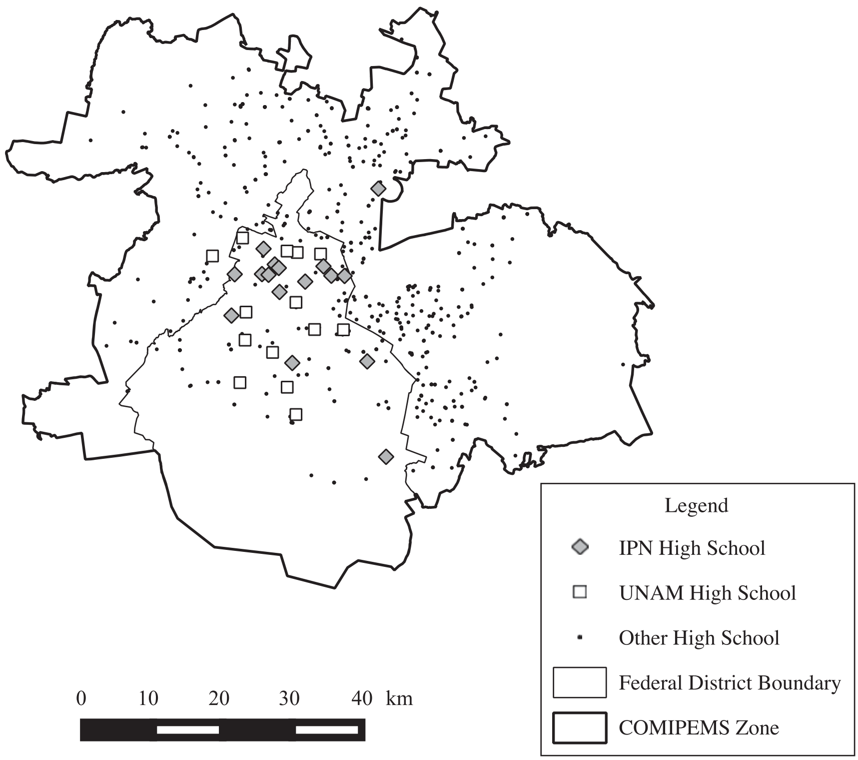

Figure 1
Map of COMIPEMS-Participating High Schools in the Metropolitan Mexico City Area

While the UNAM schools are public in a sense, this subsystem refuses to administer the ENLACE exam and is legally able to do so because of its "autonomous" status.[12] The IPN, all other public subsystems, and many private schools administer the ENLACE, the latter doing so voluntarily. Because the ENLACE data provide the dependent variables for our analysis, only the effects of admission to IPN schools are examined in this paper. We will show in the data description how students attending IPN schools differ from those in the UNAM or nonelite schools, while in the empirical results we will see what bearing IPN admission has on the peer characteristics and commuting distance that students experience.

The configuration of the high school system does not facilitate lateral transfers of students between school subsystems, which are run by numerous entities at the local,

12. An additional difference between the UNAM and other subsystems is that students selecting an UNAM school as their first choice during the COMIPEMS assignment process must take a version of the entrance exam written by UNAM, which is advertised to be equivalent to the standard version in content and difficulty.

state, and federal levels. Students who find that their current school is a bad fit cannot easily switch to a school in a different subsystem that balances academic rigor, curriculum, and other characteristics to their taste, unless they drop out of school entirely and attempt to begin anew elsewhere. Among public middle school students in our data, only 3.9 percent of students graduating within three years of COMIPEMS-taking (that is, on time) do so in a public subsystem different from the one to which they were admitted, and this figure is just 0.4 percent among IPN admittees.[13] Furthermore, among IPN admittees, whom we expect to be the most in need of transfers for academic reasons, only 2.1 percent graduate from another public subsystem regardless of time to completion, while another 1.7 percent graduate from a private school.

III. Regression Discontinuity Design and Sample Definition

The goal of this paper is to determine how much (marginal) admission to an IPN school changes students' probability of dropout and their end-of-high-school exam scores, compared to the alternative of admission to a nonelite school. Put another way, the econometric challenge is to estimate the effect on academic outcomes from admission to a school in an IPN subsystem instead of admission to the student's most-preferred nonelite choice, holding constant all student characteristics, observed and unobserved.

The COMIPEMS assignment mechanism permits a straightforward strategy for identifying the causal effect of IPN school admission on outcomes through a sharp regression discontinuity (RD) design. Each school that is oversubscribed (that is, with more demand than available seats) accepts all applicants at or above some cutoff COMIPEMS exam score and rejects all applicants scoring below that cutoff. This cutoff is set implicitly by the score of the student who obtains the final seat in that school during the sequential assignment process. If a student lists a particular school on the preference sheet and scores below the cutoff for each of the more-preferred schools, admission to that school is determined entirely by whether the student scored at or above its cutoff score.[14] This generates a sharp discontinuity in the probability of admission (from 0 to 1) when the student's score reaches the cutoff.

The desired comparison is between IPN admission and nonelite admission. Thus, we need to construct a sample of students such that assignment to "treatment" (admission to the IPN subsystem) depends solely on whether a student's COMIPEMS score exceeds a predetermined cutoff. To achieve this, we first identify, for each student, the minimum COMIPEMS exam score that the student could obtain and still be assigned to an IPN school. This student-specific IPN admission cutoff score is known because the student's

13. Another 3.0 percent graduate from a private high school, compared to 1.1 percent among IPN admittees. Disregarding time to completion, 7.9 percent of graduates do so from another public subsystem and 4.0 percent do so from a private school. This is an overestimate of the transfer rate because a small number of assigned students retake the COMIPEMS exam in the following year and are assigned to a different subsystem.

14. The elite schools automatically reject all students with a grade point average below seven out of ten. Very few students score high enough for admission and fail to meet this requirement.

stated preferences, combined with the cutoff scores for each school, fully determine the student's assignment for any point value of the COMIPEMS score.[15] If the IPN admission cutoff for a student is undefined because no COMIPEMS score would result in IPN assignment, then he is dropped from the sample.[16]

In the sharp RD design employed here, a score exceeding the IPN admission cutoff implies treatment with probability of one. To obtain this outcome in the RD sample, we exclude any student who would be admitted to a non-IPN school for any point value exceeding the IPN admission cutoff. For example, a student might select an UNAM school with a cutoff score of 80 as his first choice and an IPN school with a cutoff of 70 as his second choice. In this case, COMIPEMS scores of 80 and above would lead to UNAM assignment, while scores from 70 to 79 would lead to IPN assignment. Such students are excluded from the RD sample. This restriction implies that all students in the RD sample chose an IPN school as their most-preferred option, so we might think of the RD sample as consisting of students with a relatively strong preference for IPN schools. We show in Appendix Table C1 that relaxing this restriction by allowing UNAM or nonelite assignments above the cutoff has only a small effect on the estimated effects of IPN admission.[17]

Finally, we want to ensure that scoring below the IPN admission cutoff score leads to nonelite assignment. Although by construction no score below this cutoff can result in IPN assignment, we exclude any student whose stated choices are such that he could obtain a score below the IPN admission cutoff and still be admitted to an UNAM school.[18] This could happen if, for example, the student's first choice was an IPN school with a cutoff of 80 and his second choice was an UNAM school with a cutoff of 70. These three sample restrictions—existence of an IPN admission cutoff score, no non-IPN school assignments possible above this cutoff, and only nonelite school assignments below this cutoff—result in an RD sample where the probability of elite (IPN) assignment is zero for all COMIPEMS scores below the IPN admission cutoff and one for all COMIPEMS scores above it.

Note that different scores above the student's IPN admission cutoff could result in assignment to different IPN schools—for example, a score of 70 may be enough for one requested IPN school, while a score of 75 would be sufficient for admission to a more-preferred IPN school. This does not pose a problem for the RD design because the treatment is defined as assignment to any IPN school, not only to the school that

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15. For example, assuming the student obtains a score of 70, the student's assignment would be his highest-ranked school that has a cutoff score of 70 or below.
16. Specifically, the admission cutoff is undefined if the student has a middle school GPA below seven, if he does not list any IPN schools on his preference list, or if each listed IPN school has a non-IPN school with a lower cutoff score listed above it in the preference list. For example, suppose a student lists as choice one an UNAM school with cutoff of 70, and choice two is an IPN school with a cutoff of 80, and choice three is a nonelite school that is not oversubscribed. For scores 70 and above, the student is assigned to the UNAM school, and for scores of 69 and below he is assigned to the nonelite school. The IPN assignment is impossible because it is less-preferred but has a higher cutoff than the more-preferred choice.
17. All appendices can be found online at http://jhr.uwpress.org.
18. There are two reasons for this restriction. First, the UNAM system is elite, and we want to estimate the impact of IPN admission versus the counterfactual of nonelite admission. Second, the UNAM is missing data on graduation and test scores, so we could not include these students in the sample even if we wanted to make this comparison.

corresponds to the student's IPN admission cutoff.[19] It will be useful at times in this paper to discuss this latter school, however, which we will refer to as the "cutoff school." Similarly, different COMIPEMS scores below the cutoff may result in assignment to various nonelite schools. We will refer to the school directly below the cutoff—the school assignment for a score one point below the IPN admission cutoff—as the "next-best" school. To summarize, each student is characterized by three things: his cutoff school (the lowest-cutoff IPN school he could attend, given his choices), his next-best school (the most-preferred nonelite school he could attend if he scored too low for IPN admission), and the cutoff score such that he would always be admitted to an IPN school if his COMIPEMS score were equal to or greater than this cutoff and would never be admitted to an IPN school if his COMIPEMS score were less than the cutoff.

For each student i in the RD sample in exam year t, we index the cutoff school by j. Following Abdulkadiroglu et al. (2014), we use a stacked nonparametric RD design that estimates, for students with a score close to the relevant cutoff, a single average admission effect over all cutoff schools while controlling for separate linear terms in the COMIPEMS score for each cutoff school and cutoff school–COMIPEMS year fixed effects. The estimating equation is:

$$(1) \quad Y_{ijt} = \delta admit_i + \gamma_{1j}\,(c_i - \underline{c}_{jt}) + \gamma_{2j}\,(c_i - \underline{c}_{jt})\,admit_i + \mu_{jt} + \varepsilon_{ijt}$$

where Y_{ijt} is the outcome of interest (dropout or ENLACE exam score), $c_i - \underline{c}_{jt}$ (the "centered" COMIPEMS score) is the difference between i's COMIPEMS score and j's cutoff score in year t, and $admit_i = 1$ if $c_i - \underline{c}_{jt} \geq 0$. The parameter of interest is δ, the local average treatment effect of being admitted to an IPN school instead of a nonelite school (Imbens and Lemieux 2008). This is an intention-to-treat effect since students do not necessarily attend a school in the subsystem to which they were admitted. We do not have student-level data on enrollment to show that students actually attend their assigned school. In practice, though, compliance with elite vs. nonelite assignment among ENLACE-takers is nearly perfect. Of those in the RD sample who take the ENLACE exam, 99.8 percent of the students rejected from the IPN subsystem take the exam in a nonelite school, while 96.1 percent of ENLACE exam-takers who were admitted to an IPN school take the exam in an IPN school.

We use the bandwidth selection procedure suggested by Imbens and Kalyanaraman (2012) and, following the same authors, use the edge kernel in estimating the local linear regressions.[20] Cluster-robust standard errors allow for correlation within the high school to which the student was admitted. The running variable, centered COMIPEMS score, is discrete since the COMIPEMS exam is scored in one-point increments from zero to 128. Lee and Card (2008) suggest estimating cluster-robust standard errors with respect

19. Estrada and Gignoux (2015) also take this approach of allowing school-specific cutoffs while defining treatment as admission to the IPN system.

20. The edge kernel is $K_h\left(c_i - \underline{c}_{jt}\right) = \mathbf{1}\left(\left|c_i - \underline{c}_{jt}\right| \leq h\right)\left(1 - \frac{\left|c_i - \underline{c}_{jt}\right|}{h}\right)$, where h is the bandwidth. We select the optimal bandwidth while omitting the cutoff-year fixed effects and using a single set of piecewise-linear terms instead of separate sets for each cutoff school. Having selected the bandwidth, we estimate Equation 1 including the fixed effects and cutoff school-specific linear terms.

to the discrete values of the running variable, in order to account for specification error in the local polynomials. Because there are relatively few clusters and analytic clustered standard errors may be downward-biased in this case, wild-cluster bootstrapped p-values also are presented (see Cameron, Gelbach, and Miller 2008). We make inference based on the more conservative of the two approaches in each case.

An advantage of the RD design is that it does not require any assumptions about the decision-making process by which students choose schools and whether their rankings of schools truly represent revealed preferences. Conditional on COMIPEMS score, the admitted and rejected students near a school's cutoff have the same expected characteristics, including preferences over schools. Even if students are trying to choose strategically or making mistakes in their selections, this behavior will not differ by admissions outcome near the cutoff. We can thus remain agnostic on the issue of the distribution of student preferences and the factors that influence them.

IV. Data Description

A. Data Sources and Descriptive Statistics

The data used in this paper come from two sources, both obtained from the Subsecretariat of Secondary Education of Mexico: the registration, scoring, and assignment data for the 2005 and 2006 COMIPEMS entrance examination processes, and the scores from the 2008, 2009, and 2010 12th grade ENLACE exams.[21] The COMIPEMS dataset includes all students who registered for the exam, with their complete ranked listing of up to 20 high school preferences, basic background information such as middle school grade point average and gender, exam score out of 128 points, and the school to which the student was assigned as a result of the assignment process. It also includes student responses to a multiple choice demographic survey turned in at the time of registration for the exam.

The ENLACE dataset consists of exam scores for all students who took the test in spring 2008 (the first year that the 12th grade ENLACE was given), 2009, or 2010. The scores for both the math and Spanish sections are reported as a continuous variable, reflecting the weighting of raw scores by question difficulty and other factors. We normalize the scores by subtracting off the year-specific mean score for all examinees in public high schools within the COMIPEMS geographic area and dividing by the year-specific standard deviation from this same sample. The ENLACE scores are matched with the 2005 and 2006 COMIPEMS-takers by using the Clave Única de Registro de Población (CURP), a unique identifier assigned to all Mexican citizens. Matching is performed by name and date of birth if no CURP match is found and, following that, further matching is performed on name and assigned school. Further details regarding the ENLACE data and its validity as a proxy for dropout are given in the next subsection. We limit the sample to applicants who graduated from a public middle school in Mexico City in the year that they took the COMIPEMS exam. We exclude students from private

21. The 2010 data are used in order to match students from the 2006 COMIPEMS cohort who took four years to complete high school instead of three.

middle schools because many of these students choose to continue their education in private high schools, a decision that is endogenous to IPN admission. We expand on this issue in the next subsection.

The IPN schools are highly demanded among these students. For every seat available in an IPN school, 1.9 students list an IPN school as their first choice. Every IPN school is oversubscribed. Figure 2 shows the distribution of cutoff scores for all oversubscribed schools. Panel A shows that, along with the UNAM schools, the IPN schools have far higher cutoff scores than the vast majority of nonelite schools. Panel B weights the cutoff schools by the number of students admitted, showing that nearly all students assigned to a high-cutoff school are in the IPN or UNAM subsystems.

Table 1 presents summary statistics for the sample of all students, the subsamples of students who were assigned to the IPN, UNAM, and nonelite systems, and students meeting the criteria for inclusion in the RD sample. Students assigned to IPN schools are quite different from those at nonelite schools. The IPN's student body has higher average COMIPEMS exam scores (88.0 points vs. 57.7), grade point (8.54/10 vs. 7.96/10), parental education (11.4 years vs. 9.8), family income (5,210 pesos per month vs. 3,850), and ENLACE exam scores (1.12 normalized score vs. –0.18).[22] Students commute on average 4.33 kilometers farther to IPN schools than nonelite options.[23] While 44 percent of students assigned to nonelite schools reside in the Federal District rather than the generally poorer State of Mexico, 57 percent of IPN students are Federal District residents. Another notable contrast is that while two-thirds of IPN students are male, fewer than half of students in the nonelite subsystems are. This is due to higher preference for the IPN schools among males, perhaps because of the polytechnic focus of the curriculum. On the other hand, IPN students are similar to students from the UNAM schools on most dimensions, including COMIPEMS score, middle school GPA, and family background. Again, though, the IPN student body is more male-dominated than the UNAM.

The RD sample is described in Column 5. There are 41,075 students who meet these criteria. As expected, the mean characteristics for this group fall between the IPN and nonelite samples. How much did each restriction on the RD sample, described in Section III, affect the sample size? We start by discarding students who could not be assigned to an IPN school for any possible COMIPEMS score; 76,738 students remain. Dropping students who would be assigned to a non-IPN school for some COMIPEMS scores above the IPN admission cutoff eliminates 26,348 students. Of these, 26,161 were dropped because some COMIPEMS scores above the cutoff would result in UNAM assignment. Finally, 9,315 students are dropped because they would be assigned to an UNAM school for some COMIPEMS scores below the IPN cutoff.

B. ENLACE Taking as a Proxy for Graduation

It is clear from Table 1 that many COMIPEMS exam takers do not take the ENLACE. There is substantial evidence that observing ENLACE taking in the data is a good proxy

22. There is no binding test score ceiling for either exam. Score ceilings present a problem for academic gains because there is no way for students with the highest score to demonstrate progress. The COMIPEMS exam intentionally avoids a ceiling in order to sort students during assignment.

23. Distance is computed as the straight-line distance from the centroid of the student's postal code to the location of the assigned school.

Panel A: Unweighted Frequency

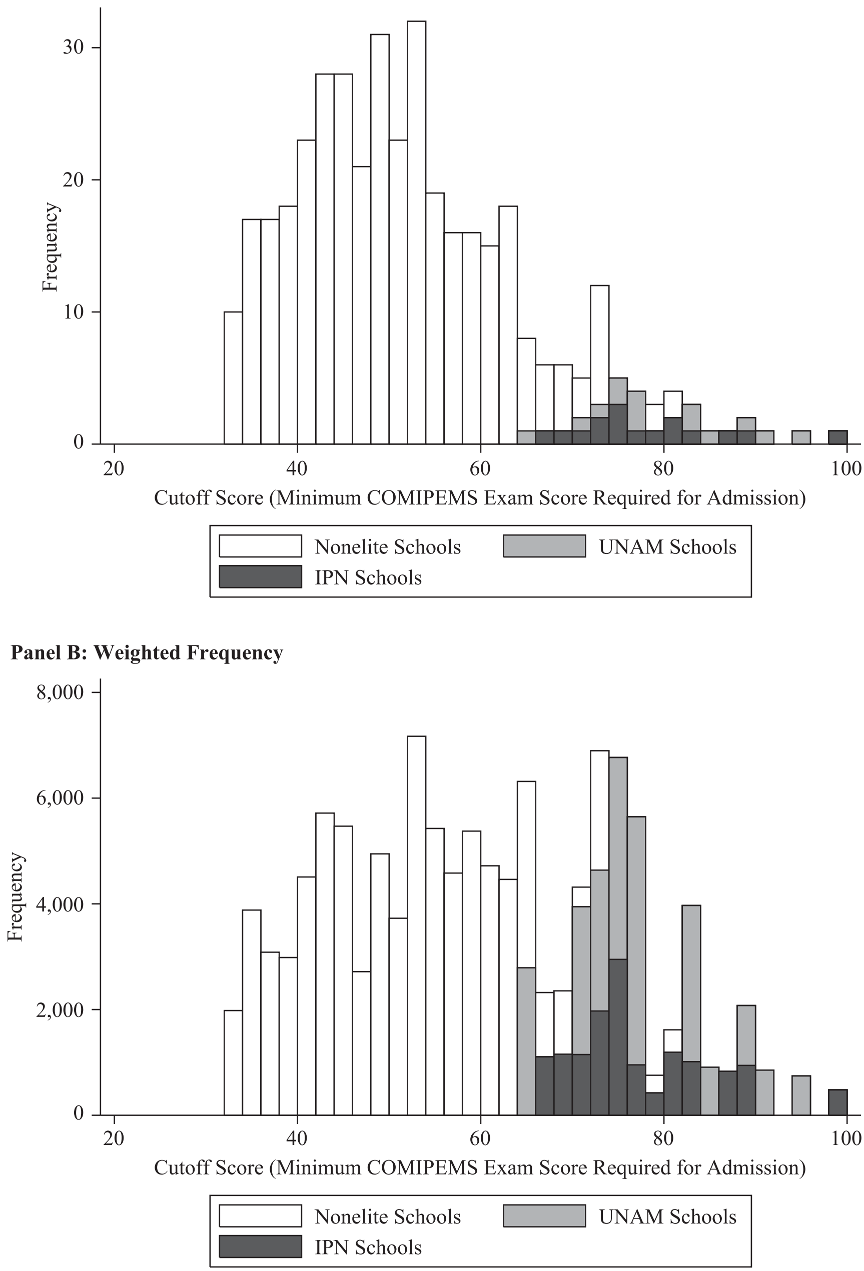


Figure 2

Distribution of Admission Cutoff Scores for Oversubscribed Schools, 2005 Exam Year

Notes: Panel B weights oversubscribed schools by the number of students assigned, so that the mass represents the number of students attending schools with the indicated cutoff score.

Table 1
Characteristics of Students Eligible for Assignment

	All Students (1)	IPN Students (2)	UNAM Students (3)	Nonelite Students (4)	RD Sample (5)
Male	0.46	0.65	0.47	0.44	0.62
	(0.50)	(0.48)	(0.50)	(0.50)	(0.49)
Maximum of mother's and father's education	10.18	11.38	11.76	9.77	10.71
	(3.35)	(3.23)	(3.40)	(3.23)	(3.25)
Family income (thousand pesos/month)[a]	4.22	5.21	5.75	3.85	4.62
	(3.35)	(3.64)	(4.08)	(3.07)	(3.38)
Hours studied per week	5.19	6.22	6.58	4.83	5.56
	(3.26)	(3.33)	(3.34)	(3.14)	(3.31)
Index of parental effort[b]	–0.03	0.12	0.18	–0.08	0.04
	(1.00)	(0.95)	(0.97)	(1.00)	(0.97)
Student is employed	0.04	0.03	0.02	0.04	0.04
	(0.19)	(0.18)	(0.15)	(0.20)	(0.20)
Middle school grade point average (of 10)	8.10	8.54	8.65	7.96	8.29
	(0.82)	(0.79)	(0.79)	(0.77)	(0.79)
Distance from assigned school (kilometers)[c]	7.14	10.66	9.40	6.33	9.22
	(6.14)	(7.36)	(6.73)	(5.60)	(7.13)
Resides in Federal District	0.48	0.57	0.66	0.44	0.50
	(0.50)	(0.49)	(0.47)	(0.50)	(0.50)
Number of schools ranked	9.31	9.82	9.45	9.23	9.72
	(3.59)	(3.75)	(3.70)	(3.55)	(3.70)
IPN school as first choice	0.15	0.90	0.03	0.10	1.00
	(0.36)	(0.30)	(0.18)	(0.30)	(0.00)
Number of IPN schools chosen	1.18	4.39	1.24	0.84	3.95
	(1.89)	(2.58)	(1.64)	(1.49)	(2.64)
UNAM school as first choice	0.49	0.10	0.97	0.45	0.00
	(0.50)	(0.30)	(0.18)	(0.50)	(0.00)
Number of UNAM schools chosen	2.53	1.96	4.88	2.20	1.24
	(2.60)	(2.17)	(2.52)	(2.44)	(1.74)
Preference ranking of assigned school (conditional of assignment)	3.30	1.69	1.90	3.80	2.73
	(2.90)	(1.52)	(1.53)	(3.08)	(2.48)
COMIPEMS examination score	63.74	87.96	85.57	57.66	74.63
	(17.95)	(11.06)	(9.90)	(14.29)	(18.49)

(*continued*)

Table 1 (*continued*)

	All Students (1)	IPN Students (2)	UNAM Students (3)	Nonelite Students (4)	RD Sample (5)
Dropped out (did not take ENLACE exam; only for non-UNAM students)	0.48 (0.50)	0.38 (0.49)		0.49 (0.50)	0.42 (0.49)
ENLACE examination score (for those who took the exam)[d]	–0.03 (0.98)	1.12 (0.86)		–0.18 (0.90)	0.50 (1.11)
Observations	354,581	28,551	46,265	279,765	41,075

Notes: Standard deviations in parentheses.
[a]Average 2005–2006 exchange rate was 10.9 pesos/dollar.
[b]The parental effort index is constructed by averaging the scores (1–4 ordinal scale) for 13 questions about parental effort and involvement from the survey filled out at the time of COMIPEMS registration. The survey asked "How often do your parents or adults with whom you live do the following activities?" for activities such as "help you with schoolwork" and "attend school events." The measure is normalized to have mean zero and standard deviation of 1 in the sample of all students.
[c]Distance is calculated as the straight-line distance between the centroid of the student's postal code and the assigned school.
[d]The normalized ENLACE examination score is constructed by subtracting off the year-specific mean score for all examinees in public high schools within the COMIPEMS geographic area and dividing by the year-specific standard deviation from this same sample.

for a student graduating from high school. Because of this, we argue that differences in ENLACE-taking rates between marginally admitted IPN students and their marginally rejected counterparts indicate true differences in graduation rates (and thus dropout rates), rather than a data problem or the rate at which graduating 12th graders in IPN schools take the ENLACE exam. The difference cannot be due to a lower rate of success in matching ENLACE takers from IPN schools to their COMIPEMS score. Of all ENLACE takers in IPN schools in 2010, 99 percent are matched successfully to their COMIPEMS scores in 2005, 2006, or 2007. Nor does the most plausible alternative explanation, that IPN schools discourage their worst students from taking the exam, resulting in lower taking rates and higher average exam scores, appear likely. The low stakes for schools and, in the early years covered in this paper, low visibility of school-level performance data, suggest little motive for such manipulation.

Still, because the increase in dropout is a key result in this paper, Appendix B presents detailed evidence that ENLACE-taking rates are informative about dropout, much of it using detailed school census data. We summarize the key points here. First, we find that most dropout in Mexico City takes place in the tenth and 11th grades, meaning that differential ENLACE taking among enrolled 12th graders would have to be very high in order to explain the observed differences in taking rates. Second, on average, 99 percent of enrolled 12th graders are registered in the fall to take the ENLACE in the spring, a rate that does not differ between IPN and nonelite schools. Third, while some of these registered students drop out or repeat 12th grade and thus do not take the ENLACE in the current year, on average schools administer the ENLACE to 98 percent as many students as they graduate in that year. Again, this figure does not differ between IPN and nonelite schools. These high registration and taking rates make it unlikely that schools are strategically administering the exam. Fourth, retaking of the ENLACE is found to be almost nonexistent in the student-level data (0.25 percent), ruling out a situation where some types of schools administer the ENLACE to all 12th graders regardless of whether they are graduating or not (and thus administer the exam twice to 12th grade repeaters). Fifth, because we exclude private middle school students from the sample, differential enrollment in private high schools (about one-third of which do not participate in the ENLACE and thus lead to students being counted as dropouts here) can have at most a very small effect on the results. Although private middle school students rejected from the IPN are shown to be much more likely to leave the public school system, this is untrue for public middle school students. Finally, we find that marginal admission to a nonelite school does not increase the probability of dropout, inconsistent with a general strategy by all schools to discourage ENLACE taking among their worst students.[24]

C. Correlates of Dropout

Dropout is predicted both by academic ability and IPN admission, as shown by the partial correlations presented in Table 2. Column 1 shows that, in the cross-section, COMIPEMS exam score and middle school grade point average (GPA) are negatively correlated with dropout. Particularly striking is the GPA coefficient, showing that a one standard deviation (0.82) increase in GPA predicts a 14 percentage point decrease in dropout probability. Parental education is negatively correlated with dropout as well, but the magnitude of the coefficient is very small compared to those of COMIPEMS score and GPA. Students taking the COMIPEMS exam in 2006 have a lower probability of taking the ENLACE in our sample, but this is mostly due to the fact that a small number of students take five years to complete high school, and we only have ENLACE data through 2010.[25] Students residing in the Federal District have an 8.7 percentage point higher probability of dropout, perhaps because there are better opportunities for dropouts in the local labor market. Column 2 adds high school fixed effects and shows that these relationships are similar within a high school, although the Federal District coefficient falls by more than half. Column 3 adds commuting distance, which is missing in about 14 percent of cases due to an inability to match students' reported postal codes with geographical coordinates. Here we see that commuting distance positively predicts dropout: a 10-kilometer increase in commute predicts a 3.0 percentage point increase in dropout probability. Column 4 shows that, conditional on listing an IPN school as one's first choice, dropout is much higher for students admitted to IPN schools than for those

24. Another unlikely explanation for the apparently higher dropout is that IPN students take longer to graduate than nonelite students. Because the ENLACE dataset used in this paper includes years 2008 through 2010, it captures COMIPEMS takers from 2005 who took four or five years to graduate, and COMIPEMS takers from 2006 who took four years to graduate, instead of the standard three years.
25. Further details are in Appendix B, Section I.

Table 2
Correlates of High School Dropout (Not Taking ENLACE Exam)

Dependent Variable: Dropout (Not Taking ENLACE Exam)*100	(1)	(2)	(3)	(4)	(5)
COMIPEMS score	−0.28***	−0.26***	−0.29***	−0.35***	−0.28***
	(0.054)	(0.034)	(0.015)	(0.045)	(0.018)
Middle school GPA	−16.56***	−16.80***	−17.41***	−16.74***	−17.50***
	(0.679)	(0.598)	(0.259)	(0.708)	(0.253)
Parental education (years)	−0.42***	−0.51***	−0.52***	−0.43***	−0.50***
	(0.055)	(0.033)	(0.037)	(0.057)	(0.041)
Family income (thousand pesos/month)	0.01	−0.12***	−0.14***	−0.00	−0.09**
	(0.060)	(0.033)	(0.038)	(0.063)	(0.041)
Male	0.07	−0.26	−0.18	−0.26	0.13
	(0.425)	(0.241)	(0.268)	(0.361)	(0.315)
Hours studied per week	−0.24***	−0.28***	−0.32***	−0.25***	−0.30***
	(0.044)	(0.037)	(0.034)	(0.045)	(0.034)
Parental effort index	−1.00***	−0.99***	−0.99***	−1.00***	−1.06***
	(0.119)	(0.095)	(0.106)	(0.120)	(0.109)

Employed	7.92***	7.59***	7.50***	7.91***	7.82***
	(0.539)	(0.501)	(0.523)	(0.534)	(0.532)
Resides in Federal District	8.65***	3.90**	2.93***	8.35***	7.46***
	(1.279)	(1.765)	(0.356)	(1.337)	(0.723)
Exam year 2006	3.85***	3.59***	3.64***	3.98***	3.85***
	(0.465)	(0.453)	(0.498)	(0.469)	(0.516)
Distance from home to school (kilometers)			0.30***		0.46***
			(0.023)		(0.030)
IPN school as first choice				−1.61***	−1.91***
				(0.486)	(0.452)
Admitted to IPN school				8.77***	6.98***
				(1.626)	(1.648)
Admitted high school fixed effects	NO	YES	YES	NO	NO
Observations	253,506	253,506	218,870	253,506	218,870
Adjusted R^2	0.118	0.150	0.148	0.120	0.123
Mean of dependent variable	48.7	48.7	46.9	48.7	46.9

Notes: Sample excludes students assigned to an UNAM high school, since these schools do not proctor the ENLACE exam used as the proxy for graduation. Standard errors, clustered at high school level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

admitted to nonelite schools. This correlation does not have a causal interpretation, however, because unobservable student attributes could affect both selection into an IPN school and dropout probability. The next section uses the RD design to establish the causal IPN admission–dropout relationship.

V. Effects of Elite School Admission

This section uses the RD design outlined in Section III to estimate the effect of marginal admission to an IPN school on the probability of dropping out of high school and, conditional on taking the ENLACE exam, on the exam score obtained.

A. School Characteristics and Commute

Before presenting the effects of IPN admission on dropout and test scores, we show that admission results in students being assigned to a school with drastically more able peers while also needing to commute a longer distance to reach their assigned school. Table 3 and corresponding Figure 3 show the results from estimating Equation 1 with peer characteristics and commute distance as the dependent variables.[26] On average, marginal IPN admission implies assignment to a school where peers scored 19.8 COMIPEMS points (more than one standard deviation) higher than the next-best school. Peers also have, on average, middle school GPAs 0.52 points (0.62 standard deviations) higher than the next-best school and have parents with 1.2 additional years of education.[27] Students also experience longer commutes due to IPN admission, traveling 4.5 kilometers farther in each direction, nearly 50 percent more than the RD sample average. Thus, IPN admission, on average, exposes students to much "better" peers while requiring a longer commute.

B. Probability of Dropout

Marginal admission to an IPN school significantly increases the probability of dropout. Figure 4 illustrates this graphically, plotting the dropout rate in a 20-point window around the IPN admission cutoff. Table 4 confirms this finding, reporting the average effect of admission on dropout estimated using Equation 1 for the optimal bandwidth (Column 1). The estimated dropout effect is large, 9.4 percentage points compared to a dropout rate of about 42 percent among marginally rejected students.[28] This result is robust across different bandwidth selections: estimates using half (Column 2) and double (Column 3) the optimal bandwidth are 9.3 and 11.0 percentage points, respectively. We note that the optimal bandwidth is 15.3 COMIPEMS points, somewhat less

26. Results from local quadratic regressions are similar for these and all other regressions in the paper.
27. Estrada and Gignoux (2015) provide evidence that IPN admission results in access to better school inputs, including somewhat smaller class sizes, more computers per student, and more full-time and college-educated teachers.
28. Our estimates for the effect of admission on dropout are larger than those found in Estrada and Gignoux (2015). Appendix Table A1 and its accompanying text give insight into these differences, but in brief, we view the difference in results as coming from differences in the samples used rather than from a difference in methods.

Table 3
Regression Discontinuity Estimates of Effect of IPN Admission on Characteristics of Assigned School

Dependent Variable	Mean COMIPEMS Score (1)	Mean Middle School GPA (2)	Mean Parental Education (Years) (3)	Distance from Home to School (Kilometers) (4)
Score ≥ cutoff	19.809***	0.520***	1.184***	4.487***
	(0.8282)	(0.0213)	(0.0694)	(0.3777)
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	18,618	22,253	19,873	22,175
Adjusted R-squared	0.788	0.766	0.648	0.102
Mean of dependent variable 1 point below cutoff	64.390	7.872	10.119	6.931
Bandwidth	13.9	16.5	14.7	17.5

Notes: Estimates are from local linear regressions, including separate linear terms for each of the 16 IPN cutoff schools and cutoff school-year fixed effects. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidth. Dependent variables in Columns 1–3 are mean characteristics of all students admitted to the student's admitted school in his admission year. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

than one standard deviation of this score in the RD sample over which this bandwidth is computed (18.49 points). Use of the edge kernel puts more weight on data near the cutoff, so 55 percent of the summed weights come from observations within five points of the cutoff score.[29]

The increase in dropout is accompanied by a higher rate of delayed high school completion, as shown in Column 4. The dependent variable in this regression is a dummy equal to one if the student either dropped out (did not take the ENLACE) or took the ENLACE more than three years after participating in the admissions process, indicating a delay of one or more years. The estimated effect of IPN admission on dropout or delay is 12.4 percentage points, three percentage points higher than the estimated impact on dropout alone. Consistent with this finding, we provide descriptive evidence in Appendix Table B1 that grade repetition rates in IPN schools are generally higher than in nonelite schools.[30]

29. Using the rectangular kernel results in almost identical estimates, as we show in Appendix Table C2.
30. We also estimate the dropout effect of admission among students whose next-best assignment is to a "bachillerato tecnológico" (technical baccalaureate) school. This is the same classification as the IPN schools and indicates that their curricula split the difference between strictly academically oriented and vocational focuses. The estimated dropout effect, presented in Appendix Table C3, is somewhat larger than in the full sample results. Thus it seems that it is not the broad curricular focus per se that drives the dropout effect.

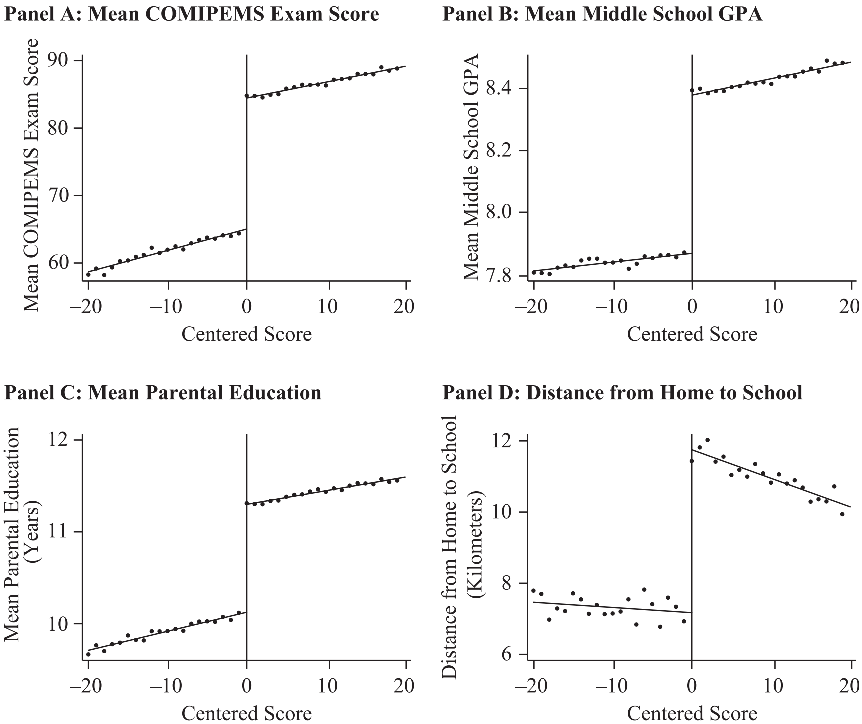


Figure 3
Effect of IPN Admission on School Characteristics Experienced by Student
Notes: Plots are for students belonging to the regression discontinuity sample defined in the text.

There is important heterogeneity behind the average effect of IPN admission on dropout. Table 5 presents these results, which are estimated using the following equation:

$$(2)\quad Y_{ijt} = \delta admit_i + \gamma_{1j}(c_i - \underline{c}_{jt}) + \gamma_{2j}(c_i - \underline{c}_{jt})\, admit_i + \mu_{jt} + z_{ijt}\left[\alpha + \widetilde{\delta} admit_i + \widetilde{\gamma}_{1j}(c_i - \underline{c}_{jt}) + \widetilde{\gamma}_{2j}(c_i - \underline{c}_{jt})\, admit_i\right] + \varepsilon_{ijt}$$

where z_{ijt} is a demeaned covariate representing some dimension of heterogeneity in the admission effect.

Students with lower middle school GPAs experience a higher increase in dropout probability. The estimates in Column 1 indicate the effect of admission on dropout decreases by 4.8 percentage points for each additional grade point. This suggests that an important driver of dropout for (marginal) IPN students is the academic difficulties that accompany being a relatively weak student in a demanding school. Column 2 fails to find any heterogeneity with respect to parental education level.

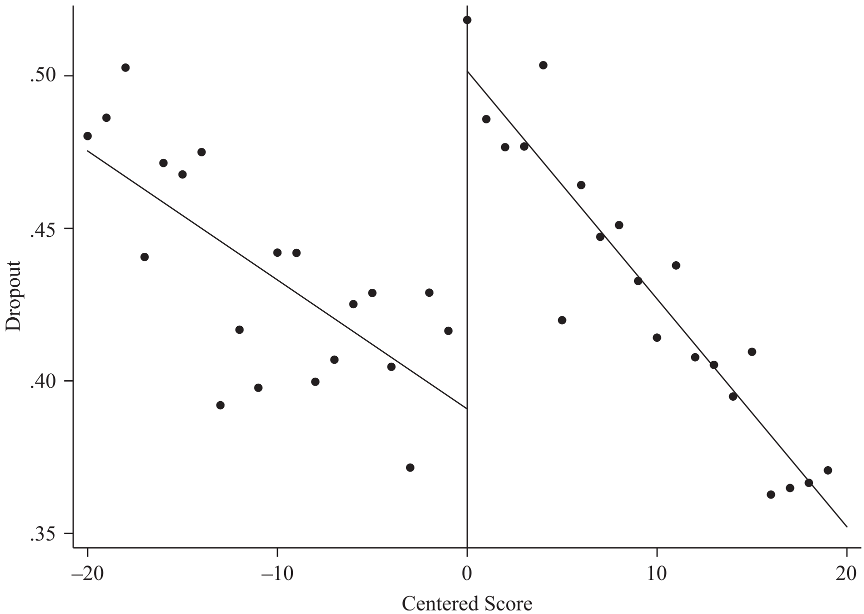


Figure 4

Effect of IPN Admission on Dropout Probability

Notes: Dropout is defined as not taking the ENLACE exam. Plot is for students belonging to the regression discontinuity sample defined in the text.

Table 4

Regression Discontinuity Estimates of Effect of IPN Admission on Dropout

	Dropout (Not Taking ENLACE Exam)			Dropout or Late ENLACE (4+ Years)		
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Score ≥ cutoff	0.094***	0.093***	0.110***	0.124***	0.121***	0.144***
	(0.0167)	(0.0202)	(0.0150)	(0.0174)	(0.0220)	(0.0172)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	20,281	11,122	35,475	17,748	9,783	32,658
Adjusted R-squared	0.014	0.018	0.016	0.022	0.026	0.021
Mean of dependent variable 1 point below cutoff	0.416	0.416	0.416	0.490	0.490	0.490
Bandwidth	15.3	7.6	30.6	13.5	6.7	26.9

Notes: Estimates are from local linear regressions, including separate linear terms for each of the 16 IPN cutoff schools and cutoff school-year fixed effects. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidth. Standard errors clustered at the school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5

Regression Discontinuity Estimates of Heterogeneous Effects of IPN Admission on Dropout

Dependent Variable: Dropout (Not Taking ENLACE Exam)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Score ≥ cutoff	0.092*** (0.0169) [0.00]	0.095*** (0.0164) [0.00]	0.105*** (0.0173) [0.00]	0.107*** (0.0165) [0.00]	0.093*** (0.0167) [0.00]	0.108*** (0.0178) [0.00]	0.106*** (0.0171) [0.00]
(Score ≥ cutoff) * (Middle school GPA)	–0.048*** (0.0179) [0.03]					–0.064** (0.0266) [0.00]	–0.052** (0.0212) [0.00]
(Score ≥ cutoff) * (Parental education)		–0.005 (0.0044) [0.21]				–0.008 (0.0052) [0.16]	
(Score ≥ cutoff) * (Change in commute due to admission)			0.005*** (0.0020) [0.03]			0.007*** (0.0022) [0.04]	0.005*** (0.0020) [0.02]
(Score ≥ cutoff) * change in mean HS peer COMIPEMS exam score due to admission)				0.003 (0.0019) [0.03]		0.003* (0.0019) [0.00]	

(Score ≥ cutoff) * (Student resides in Federal District)					–0.026 (0.0323) [0.36]	0.004 (0.0421) [0.94]	
(Score ≥ cutoff) * (Middle school GPA) * (Change in commute due to admission)							–0.010*** (0.0029) [0.00]
Observations	20,259	20,614	13,567	13,589	20,281	11,435	13,550
Adjusted R-squared	0.098	0.016	0.022	0.019	0.019	0.110	0.108
Mean of dependent variable 1 point below cutoff	0.415	0.408	0.403	0.402	0.416	0.397	0.401
Bandwidth	15.5	16.5	13.4	12.4	15.3	12.2	13.0

Notes: Estimates are from local linear regressions, including separate linear terms for each of the 16 IPN cutoff schools, cutoff school-year fixed effects, and covariates whose interaction terms are included in the regression. Piecewise-linear terms in centered COMIPEMS score are interacted with the corresponding demeaned covariate in each column. Column 7 includes the interaction of the demeaned middle school GPA and change in commuting distance variables, and this measure's interaction with piecewise-linear terms in centered COMIPEMS score. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidths. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 3 gives results for the differential effects with respect to changes in commuting distance. The "change in commute" variable is constructed by subtracting the commuting distance to the next-best school from the commuting distance to the IPN cutoff school. The longer the commute induced by admission, the higher the effect on dropout: an additional kilometer of one-way commuting distance increases the probability of dropout by 0.5 percentage points. In order to understand whether this commuting effect is unique to IPN admission, in Appendix Table C4 we estimate the differential effect of admission with respect to distance for the full set of nonelite oversubscribed schools. The differential effect for that set of schools is 0.004 (SE = 0.0011), similar to the finding from the IPN cutoff schools. It seems, then, that the differential effect of admission with respect to commuting distance is a general result in this sample.[31]

Column 4 repeats the commuting distance differential construction exercise, except that now the differential is with respect to the mean COMIPEMS scores of the incoming high school cohort. We do not find evidence of heterogeneity with respect to this peer ability measure. Column 5 finds no differential effect for students residing in the Federal District, which is in general more prosperous than the neighboring State of Mexico and contains all but one of the IPN schools.[32] Column 6 jointly estimates the differential effects and finds that the changes in estimated coefficients are small.[33]

To test for the possibility that increased commuting distance and low academic ability interact to increase dropout risk even more than each factor does by itself, we estimate Equation 2 including both demeaned middle school GPA and demeaned change in commuting distance, along with their interaction and the interaction of this term with the piecewise-linear centered COMIPEMS terms and the admission dummy. Column 7 shows that the coefficient on the triple interaction admission term is negative and significant, indicating that low GPA and longer commuting distance interact to make a student more likely to drop out. For example, if we compare the effects of a 4.49 km increase in commute (the average induced by IPN admission) between students with a one-point difference in GPA, the student with the lower GPA will suffer an additional 4.5 percentage point (–0.010 * 4.49 * –1) increase in dropout probability.

These results make clear that dropout is systematically related to IPN admission, and its interaction with academic ability as proxied by middle school GPA. Students admitted to an IPN school are on average more likely to drop out and thus less likely to take the ENLACE, such that even after conditioning on COMIPEMS score, IPN admittees

31. To test whether this differential came from different IPN schools having both higher admission effects on dropout and commute, we reestimated this equation while including one admission dummy variable per cutoff school. This identifies the commuting effect based off of within-cutoff heterogeneity in commuting changes. Results are nearly identical.

32. Appendix Table C5 further restricts the sample to the boroughs that make up the "core" of the Federal District and contain 14 of 16 IPN schools. Results are similar to the full-sample estimates.

33. We explore further potential dimensions of heterogeneity (family income, hours per week spent studying, and average middle school GPA and COMIPEMS exam score) in Appendix Table C6. There is no evidence of differential effects with respect to these covariates. It is worth noting that family income and time spent studying are likely to have significant measurement error given that they are self-reported. Appendix Table C7 controls for measures of student preferences as a robustness check and estimates the differential effect of admission with respect to whether the cutoff school was the student's first choice. The evidence is weak, but suggests larger effects when the cutoff school is the first choice.

taking the ENLACE have higher middle school GPAs. To show this, we estimate the following equation for each of the student characteristics x_{ijtk}:

$$(3) \quad x_{ijtk} = \phi_k admit_i + \beta_{1jk}(c_i - \underline{c}_{jt}) + \beta_{2jk}(c_i - \underline{c}_{jt})\, admit_i + \mu_{jtk} + \varepsilon_{ijtk}.$$

If x_k is balanced across the cutoff, then ϕ_k should be close to zero. Table 6, Panel A and accompanying Figure 5 give estimates at the time of assignment (prior to dropout), where we expect balance. Of the seven covariates tested, none are found to change discontinuously at the cutoff. When estimating the equations jointly using seemingly unrelated regression and performing a joint test for discontinuities, we fail to reject the null hypothesis of no discontinuity ($p = 0.46$). Panel B, however, shows that within the sample of ENLACE takers middle school GPA is unbalanced (about 1/10 standard deviations higher for admitted students) as well as hours studied per week in middle school. The joint test of discontinuities is rejected at the 0.01 significance level. Hence dropout among marginally admitted students is not only higher than among the rejected, but is also heterogeneous with respect to student characteristics. This differential dropout may bias upward estimates of the IPN admission effect on ENLACE exam scores if the additional dropout is among the students who would have the lowest ENLACE scores. We will estimate bounds of the ENLACE effects that account for this possibility.

C. ENLACE Exam Performance

We now turn to the effect of IPN admission on the standardized ENLACE exam score. We first ignore the differential dropout issue raised in the previous section and then bound the effects while accounting for dropout. Using all observed scores, Figure 6 suggests that there is a large, positive effect of IPN admission on ENLACE math scores and a much smaller positive effect on Spanish scores. This result may be unsurprising given that IPN schools focus heavily on mathematics, engineering, and the sciences in their curriculum. Table 7 reports the RD estimates of these relationships for the optimal bandwidth (Columns 1 and 4) and both half and double this bandwidth (Columns 2 and 5, and 3 and 6, respectively). Again, the results are robust to the choice of bandwidth: The estimated effects on math scores range from 0.22 to 0.25 standard deviations, while the Spanish estimates range from 0.04 to 0.05 standard deviations but are statistically insignificant.

We address the potential for bias due to differential dropout in two ways.[34] First, we apply the sharp bounds approach proposed by Lee (2009) to the RD design. In the context of a randomized controlled trial, the Lee bounds process begins by estimating the degree of differential attrition between treatment and control groups, trimming observations from the group (treatment or control) with lower attrition in order to balance the post-trimming attrition rates. In the case that attrition is higher in the treatment group (as in our case), trimming is accomplished either by dropping control observations with the lowest values of the outcome variable (to obtain a lower bound on the treatment effect) or with the highest values (to obtain an upper bound). Estimation of

34. The high rate of dropout in the sample makes Horowitz and Manski (2000) nonparametric bounds uninformative.

Table 6
Tests for Balance of Baseline Covariates with Respect to IPN Assignment

Dependent Variable	Middle School GPA (1)	Parental Education (2)	Family Income (Thousand Pesos/Mo) (3)	Male (4)	Hours Studied per Week (5)	Parental Effort Index (6)	Employed (7)
Panel A. At Time of Assignment							
Score ≥ cutoff	–0.019	0.091	0.091	–0.002	0.090	–0.036	–0.000
	(0.0199)	(0.0915)	(0.0903)	(0.0137)	(0.0946)	(0.0260)	(0.0052)
	[0.09]	[0.28]	[0.30]	[0.86]	[0.32]	[0.23]	[0.93]
Observations	27,136	18,414	18,188	25,007	19,519	17,351	21,007
Adjusted R-squared	0.069	0.017	0.012	0.096	0.014	0.003	0.001
Mean of dependent variable 1 point below cutoff	8.23	10.63	4.36	0.64	5.38	0.10	0.04
Standard deviation of dependent variable	0.71	3.28	2.95	0.48	3.26	0.97	0.20
Bandwidth	21.2	15.2	15.2	18.8	15.9	13.7	17.6
p-value, joint significance of all admission coefficients	0.46						

Panel B. After Dropout							
Score ≥ cutoff	0.074***	0.182	0.113	–0.011	0.272***	0.046	–0.001
	(0.0227)	(0.1110)	(0.1178)	(0.0163)	(0.1033)	(0.0330)	(0.0054)
	[0.00]	[0.15]	[0.35]	[0.37]	[0.03]	[0.23]	[0.87]
Observations	17,752	15,782	12,815	18,289	16,242	11,160	16,253
Adjusted R-squared	0.105	0.028	0.016	0.102	0.025	0.004	0.000
Mean of dependent variable 1 point below cutoff	8.39	10.75	4.36	0.60	5.65	0.09	0.04
Standard deviation of dependent variable	0.69	3.32	2.93	0.49	3.30	0.98	0.19
Bandwidth	25.1	23.6	18.9	26.2	24.7	16.4	26.1
p-value, joint significance of all admission coefficients	0.00						

Notes: Estimates are from local linear regressions of the specified order, including separate linear terms for each of the 16 IPN cutoff schools and cutoff school-year fixed effects. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidths. The p-values for joint significance are from chi-square tests that the admission coefficients are all equal to zero, estimated using seemingly unrelated regression. "At time of assignment" refers to all students in the RD sample, while "after dropout" is restricted to students who took the ENLACE exam. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

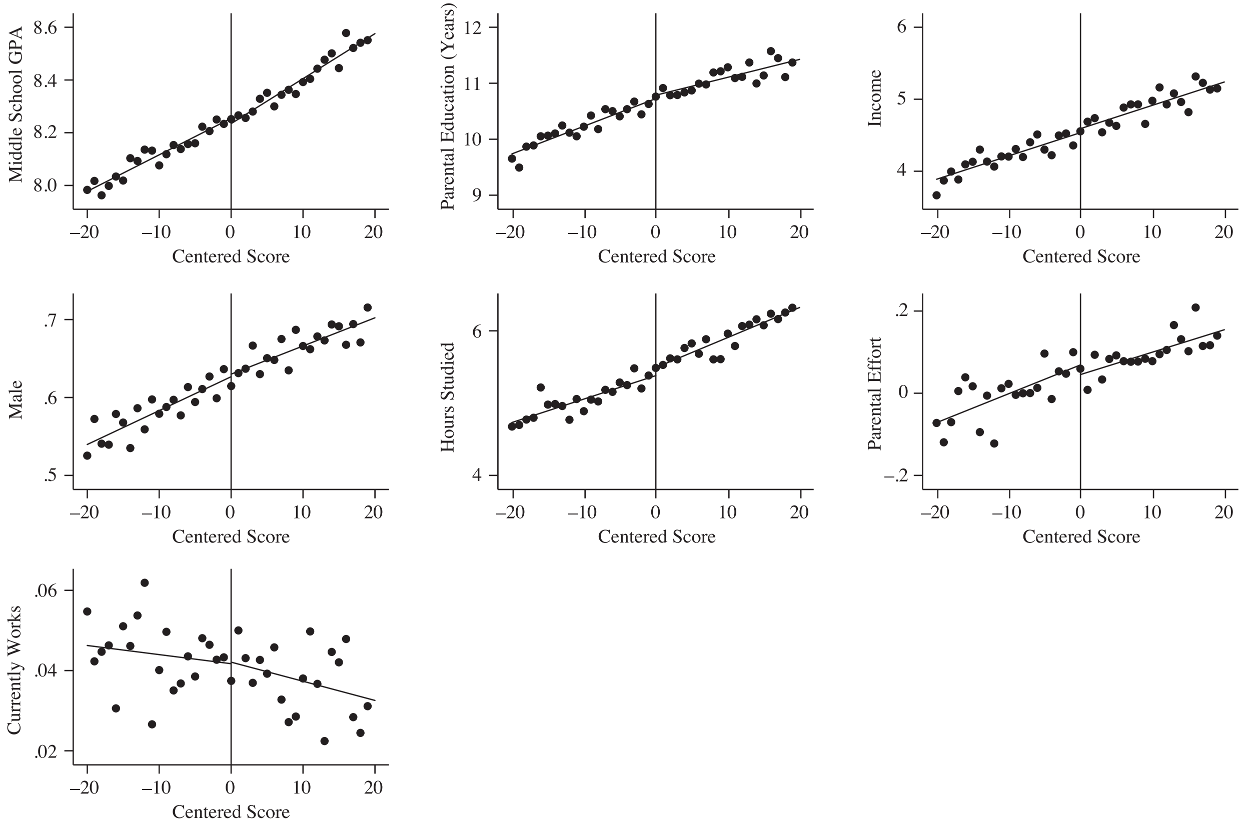
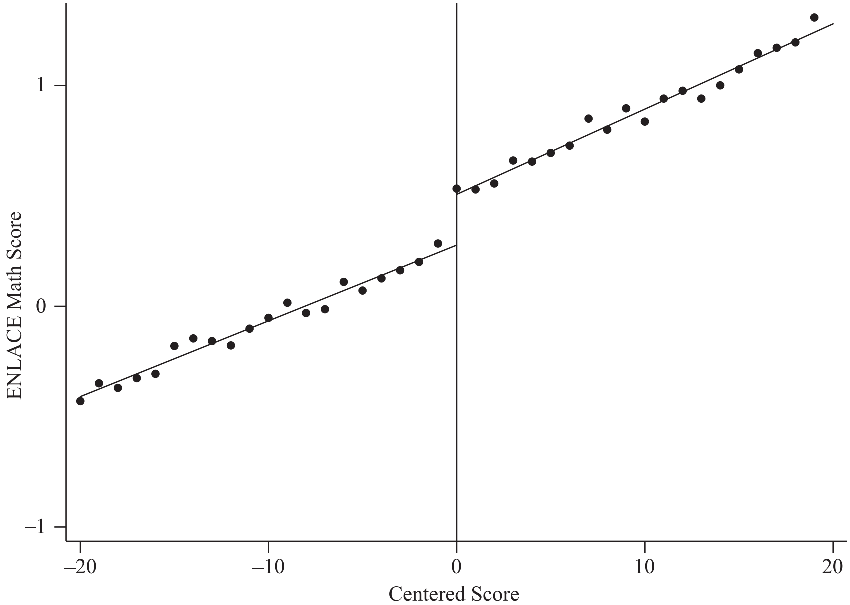


Figure 5

Balance of Baseline Covariates with Respect to IPN Admission

Notes: Dependent variables are indicated on the vertical axes. Plots are for students belonging to the regression discontinuity sample defined in the text.

Panel A: Math Score



Panel B: Spanish Score

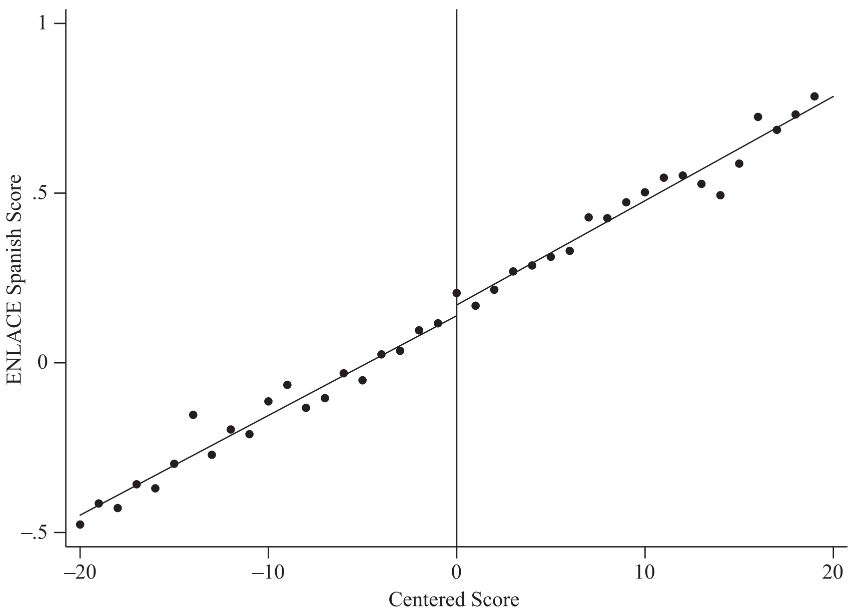


Figure 6

Effect of IPN Admission on End-of-High-School ENLACE Exam Scores

Notes: Plot is for students belonging to the regression discontinuity sample defined in the text.

Table 7
Regression Discontinuity Estimates of Effect of IPN Admission on ENLACE Score

	Math score			Spanish score		
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Score ≥ cutoff	0.246***	0.224***	0.251***	0.046	0.048	0.037
	(0.0356)	(0.0451)	(0.0293)	(0.0342)	(0.0426)	(0.0297)
	[0.00]	[0.00]	[0.00]	[0.04]	[0.32]	[0.01]
Observations	12,115	6,183	20,386	10,693	5,417	19,155
Adjusted R-squared	0.251	0.184	0.397	0.155	0.132	0.238
Mean of dependent variable 1 point below cutoff	0.284	0.284	0.284	0.117	0.117	0.117
Bandwidth	15.6	7.8	31.3	14.1	7.1	28.2
Lee bound (upper)	0.369***	0.343***	0.387***	0.159***	0.155***	0.171***
	(0.0380)	(0.0534)	(0.0247)	(0.0397)	(0.0545)	(0.0286)
Lee bound (lower)	0.118***	0.095*	0.100***	–0.114***	–0.116**	–0.144***
	(0.0373)	(0.0554)	(0.0220)	(0.0439)	(0.0535)	(0.0315)

Notes: Estimates are from local linear regressions of the specified order, including separate linear terms for each of the 16 IPN cutoff schools and cutoff school-year fixed effects. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidth. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the original relationship of interest is then carried out using the trimmed sample in order to obtain bounds on the treatment effect. In order to apply this procedure to an RD design, we assume that the dropout effect is constant within the selected bandwidth. This allows us to trim the same proportion of rejected students for each value of the centered COMIPEMS score, since excess dropout was among the admitted students. We then carry out the RD estimation procedure with the trimmed sample. Standard errors are bootstrapped, where each repetition includes the dropout effect stage, the subsequent trimming based on the estimated differential dropout, and the final estimation of the lower bound.

Estimated upper and lower bounds are found in the bottom rows of Table 7. Despite the extreme approach of trimming the worst-performing students, the lower bound of the effect on math scores is large and strongly significant: 0.12 (SE = 0.04). The Spanish bound is negative: –0.11 (SE = 0.04), as expected since the original point estimate was small. We assess the robustness of the bounding procedure in Appendix Table C2 by implementing it with the rectangular kernel and a range of bandwidths. Even when the bandwidth is very small, so that the extrapolation of the attrition rate is over only a small range, the estimated bounds are very similar.

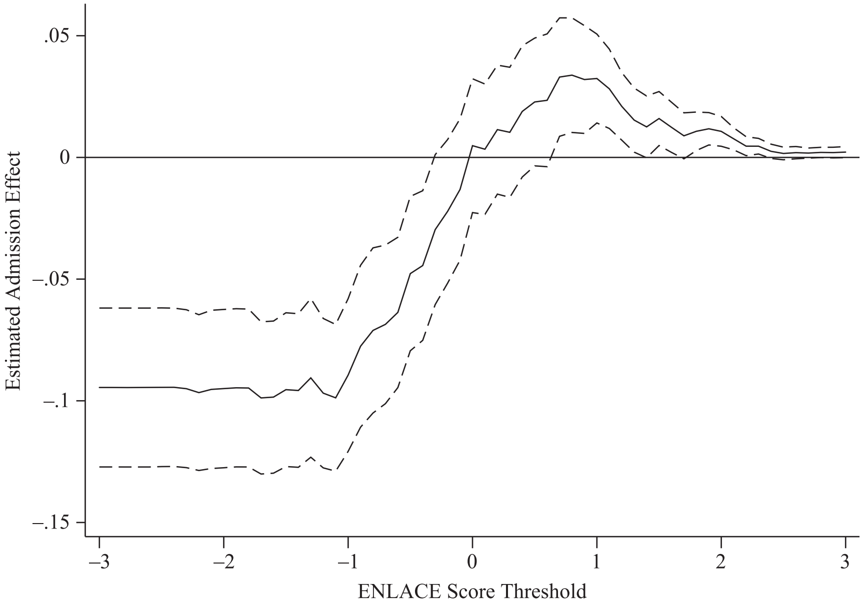
A second approach is to estimate the effect of admission on the joint probability of taking the ENLACE exam and obtaining at least a prespecified "threshold" score on the exam. This is equivalent to imputing an arbitrarily negative score for nontakers and estimating the effect of admission on the probability of exceeding an ENLACE score threshold. The motivation for this exercise is that while IPN admission decreases the probability of graduation, it is possible that admission increases the probability (unconditional on graduation) of graduating with a high exam score. After fixing a threshold ENLACE score, the standard local linear regression in Equation 1 is estimated with the joint ENLACE taking–exceeding threshold measure as the dependent variable. Figure 7 shows the estimated admission coefficients, estimated for a range of different fixed values of the threshold score. The math score effects in Panel A are positive beginning at a score of 0 and are significant for scores in the range 0.7–2.3. As expected, the Spanish effects in Panel B are negative for most scores, although the point estimates do become positive at a score of 1.3. Hence, for math scores in particular, the results are consistent with elite admission increasing the probability of graduating with a high ENLACE score while simultaneously increasing dropout and therefore decreasing the probability of graduating with a low score.

The dropout results showed striking heterogeneity with respect to middle school GPA and changes in commuting distance. We repeat this exercise for ENLACE scores in Table 8, interpreting with caution because these estimates may be biased due to the differential dropout that has been documented thus far. While we are unable to detect any heterogeneity in the admission effects on math scores, we do find that admission increases Spanish scores more for students with lower GPAs and for students with relatively more favorable commutes due to admission. The differential effect with respect to GPA may indicate that IPN schools induced catchup among lower-ability students, but it is also consistent with differential dropout among the lowest ability of the low-GPA students. When we apply the Lee bounding procedure while allowing for heterogeneity in the dropout effect, we cannot reject heterogeneous effects of elite admission on exam scores with respect to GPA that are positive (consistent with stronger students learning more, in addition to being less likely to drop out) or negative (consistent with weaker students learning more from a more rigorous curriculum that also increases their dropout risk).[35] The differential effect with respect to commuting distance may be due to the effects of a shorter commute, or it could simply reflect a different composition of schools that are close to and far from the IPN schools.[36] Thus,

35. We apply the Lee bounding procedure in the case of heterogeneous effects in the following way. First, following Lee (2009), we allow the dropout effect to differ with respect to the heterogeneity covariate. This is implemented by partitioning the RD sample into four groups, divided by the quartiles of the values of the covariate, and then obtaining RD estimates of the dropout effect separately for each quartile. In the case that the covariate is a dummy (Federal District residence), two groups are used instead of four. The ENLACE score sample is then trimmed for each of the four groups by the proportion of the corresponding estimated dropout effect. The RD specification is then estimated on the trimmed sample. Standard errors are bootstrapped as described earlier in this section. Note that this exercise does not generate sharp bounds on the interaction terms themselves, but rather it gives the estimated heterogeneous effects under Lee's (2009) extreme assumptions about differential attrition that are used to bound average treatment effects.

36. We find no evidence of a differential effect of commuting distance on either ENLACE subject score in the sample of all nonelite cutoff schools, as shown in Appendix Table C4. This suggests that distance per se is probably not causing the differential effect of distance on Spanish scores seen in the IPN schools.

Panel A: Math Score



Panel B: Spanish Score

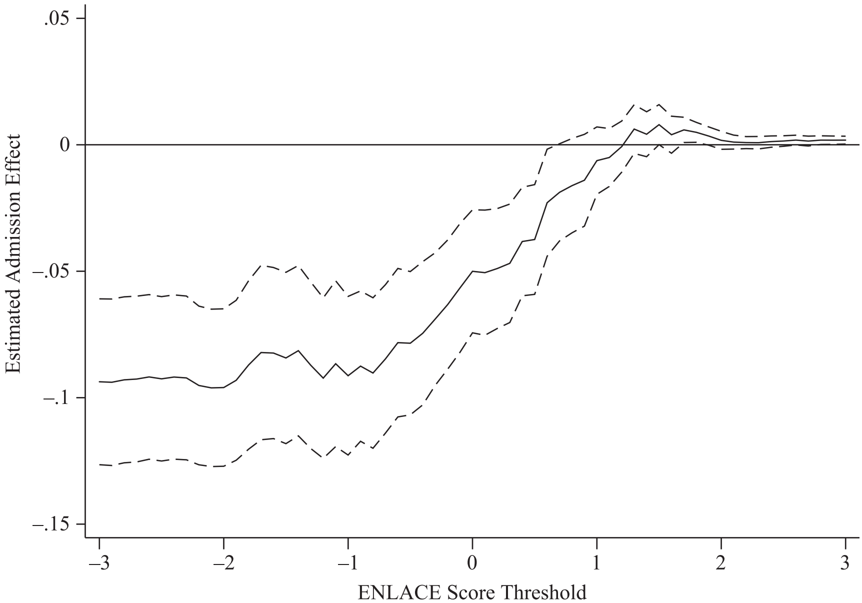


Figure 7

Effect of IPN Admission on Probability of Taking ENLACE and Scoring above Thresholds

Notes: Solid line represents RD estimates of the effect of admission on joint probability of taking the ENLACE exam and scoring above the score given on the x-axis. Dashed lines give the 95 percent confidence interval for these estimates.

Table 8
Regression Discontinuity Estimates of Heterogeneous Effects of IPN Admission on ENLACE Subject Scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Score ≥ cutoff	0.242***	0.253***	0.243***	0.226***	0.247***	0.245***	0.240***
	(0.0357)	(0.0324)	(0.0419)	(0.0425)	(0.0345)	(0.0407)	(0.0423)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
(Score ≥ cutoff) * (middle school GPA)	–0.022					–0.068	–0.042
	(0.0401)					(0.0607)	(0.0537)
	[0.43]					[0.29]	[0.25]
(Score ≥ cutoff) * (parental education)		–0.007				–0.002	
		(0.0079)				(0.0112)	
		[0.36]				[0.88]	
(Score ≥ cutoff) * (change in commute due to admission)			–0.006			–0.007	–0.005
			(0.0048)			(0.0049)	(0.0052)
			[0.24]			[0.09]	[0.33]
(Score ≥ cutoff) * change in mean HS peer COMIPEMS exam score due to admission)				0.002		0.003	
				(0.0036)		(0.0037)	
				[0.27]		[0.29]	
(Score ≥ cutoff) * (Student resides in Federal District)					–0.013	–0.086	
					(0.0558)	(0.0763)	
					[0.73]	[0.31]	
(Score ≥ cutoff) * (Middle school GPA) * (Change in commute due to admission)							–0.007
							(0.0056)
							[0.15]

(*continued*)

Table 8 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Observations	12,105	12,926	8,177	8,245	12,115	7,001	8,172
Adjusted R-squared	0.255	0.287	0.248	0.241	0.257	0.259	0.253
Mean of dependent variable 1 point below cutoff	0.286	0.272	0.340	0.323	0.284	0.325	0.340
Bandwidth	15.6	19.4	13.6	13.4	15.6	13.4	13.7
Interaction term from Lee upper bound exercise[a]	−0.090*	−0.006	−0.001	0.006	−0.035		
	(0.051)	(0.009)	(0.005)	(0.005)	(0.080)		
Interaction term from Lee lower bound exercise	0.034	−0.010	−0.007	0.003	0.013		
	(0.045)	(0.009)	(0.005)	(0.004)	(0.078)		
Panel B. Spanish Score							
Score ≥ cutoff	0.058	0.038	0.053	0.039	0.050	0.057	0.065
	(0.0358)	(0.0362)	(0.0395)	(0.0369)	(0.0336)	(0.0417)	(0.0418)
	[0.06]	[0.11]	[0.09]	[0.12]	[0.03]	[0.12]	[0.12]
(Score ≥ cutoff) * (middle school GPA)	−0.107**					−0.134**	−0.092**
	(0.0440)					(0.0530)	(0.0396)
	[0.00]					[0.01]	[0.01]
(Score ≥ cutoff) * (parental education)		0.006				0.010	
		(0.0118)				(0.0133)	
		[0.76]				[0.56]	
(Score ≥ cutoff) * (change in commute due to admission)			−0.015***			−0.018***	−0.007*
			(0.0047)			(0.0051)	(0.0036)
			[0.01]			[0.01]	[0.14]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Score ≥ cutoff) * change in mean HS peer COMIPEMS exam score due to admission)				0.006* (0.0032) [0.05]		0.005 (0.0035) [0.13]	
(Score ≥ cutoff) * (student resides in federal district)					0.032 (0.0807) [0.53]	–0.131* (0.0772) [0.07]	
(Score ≥ cutoff) * (middle school GPA) * (change in commute due to admission)							–0.017*** (0.0062) [0.09]
Observations	10,687	9,755	8,184	8,805	10,693	7,471	8,179
Adjusted R-squared	0.164	0.154	0.163	0.160	0.158	0.174	0.173
Mean of dependent variable 1 point below cutoff	0.114	0.133	0.137	0.136	0.117	0.162	0.137
Bandwidth	14.1	13.9	14.1	14.2	14.1	14.0	14.1
Interaction term from Lee upper bound exercise[a]	–0.174*** (0.047)	0.003 (0.013)	–0.012** (0.005)	0.009** (0.004)	0.010 (0.085)		
Interaction term from Lee lower bound exercise	–0.014 (0.046)	0.007 (0.013)	–0.015*** (0.006)	0.007* (0.004)	0.066 (0.080)		

Notes: Estimates are from local linear regressions, including separate linear terms for each of the 16 IPN cutoff schools, cutoff school-year fixed effects, and covariates whose interaction terms are included in the regression. Piecewise-linear terms in centered COMIPEMS score are interacted with the corresponding demeaned covariate in each column. Column 7 includes the interaction of the demeaned middle school GPA and change in commuting distance variables, and this measure's interaction with piecewise-linear terms in centered COMIPEMS score. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidths. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a]Estimation of interaction terms obtained from bounding exercise is described in Section V of the text.

we interpret the heterogeneity results as suggestive but not conclusive evidence regarding the mechanisms through which elite admission affects exam scores.

D. Effects of Admission to a Higher-Cutoff IPN School

In order to gain further insight into why IPN admission affects dropout and test scores, we briefly investigate the effects of being admitted to a higher-cutoff IPN school, compared to the counterfactual of admission to a lower-cutoff IPN school. We begin with the already-described RD sample and identify, separately for each IPN school, the corresponding school-specific sample. The sample for IPN school *A* consists of students whose counterfactual assignment is to *A* for COMIPEMS score equal to *A*'s cutoff score and whose counterfactual assignment is to another IPN school for the COMIPEMS score one point below *A*'s cutoff. These are students who, very near the cutoff score, are either barely admitted to *A* or barely rejected and sent to a different IPN school. Having constructed such a sample for each IPN school, we stack the school-specific samples and estimate Equation 1.

Table 9 begins by showing that admission to a higher-cutoff IPN school results in a somewhat different peer group: The mean peer COMIPEMS score is 4.7 points higher (compared to the 20 point jump from non-IPN to IPN schools), while mean peer middle school GPA is 0.12 points greater and peers' parents have on average 0.3 years more of education. On average, students commute 2.3 kilometers less due to admission, in contrast with the increased commute due to admission at the IPN–non-IPN boundary. The point estimate for the effect of admission on dropout is two percentage points, but the 95 percent confidence interval ranges from −1.7 to 5.5 percentage points. Thus, it is unclear how admission to a "better" IPN school affects dropout probability, except that we can rule out effects as large as those from the non-IPN to IPN comparison.[37] On the other hand, the estimated admission effects on ENLACE math and Spanish scores are 0.075 and 0.061 standard deviations, respectively, and both are significantly different from zero. It seems that students do benefit marginally from attending a higher-cutoff IPN school, at least in terms of ENLACE performance.

E. Effects of Admission to a Competitive Nonelite School

There exist schools outside the elite subsystems that have fairly high cutoff scores, as Figure 2 shows. In the interest of understanding whether the admission effects we have found are particular to elite schools, or if they pertain more generally to schools with relatively high cutoff scores, we explore the effects of admission to nonelite schools with cutoff scores at least as high as the lowest-cutoff IPN school (66 points). To do so, we identify for each of these schools the sample of students who, due to their stated preferences, would be admitted to that school if they obtained (exactly) the cutoff score. Note that, for this sample, there is a sharp change in the probability of assignment to the cutoff school at the cutoff score, from exactly 0 to exactly 1. While higher scores

37. The small point estimate for the dropout effect is consistent with all IPN schools having a challenging curriculum that increases dropout probability, with limited marginal dropout risk increases in higher-cutoff IPN schools.

Table 9
Regression Discontinuity Estimates of Effect of Admission to a Higher-Cutoff IPN School

Dependent Variable	Mean COMIPEMS Score (1)	Mean Middle School GPA (2)	Mean Parental Education (yrs.) (3)	Distance from Home to School (km) (4)	Dropout (Not Taking ENLACE Exam) (5)	ENLACE Math Score (6)	ENLACE Spanish Score (7)
Score ≥ cutoff	4.698***	0.115***	0.292***	−2.265***	0.019	0.075**	0.061**
	(0.6711)	(0.0194)	(0.0679)	(0.6203)	(0.0182)	(0.0330)	(0.0258)
	[0.01]	[0.00]	[0.00]	[0.00]	[0.27]	[0.02]	[0.07]
Observations	7,350	7,350	7,350	9,820	13,215	9,237	10,084
Adjusted R-squared	0.758	0.753	0.694	0.051	0.016	0.314	0.208
Mean of dependent variable 1 point below cutoff	84.554	8.384	11.382	12.895	0.426	0.744	0.320
Bandwidth	5.1	4.6	5.4	7.5	8.7	11.5	12.1

Notes: Estimates are from local linear regressions, including separate linear terms for each of the 15 IPN schools (excludes lowest-cutoff IPN school) and cutoff school-year fixed effects. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidth. Dependent variables in Columns 1–3 are mean characteristics of all students admitted to the student's admitted school in his admission year. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

may result in assignment to more-preferred schools, the sharp change in assignment probability at the cutoff allows us to apply the sharp RD design. We then stack the samples for each cutoff school and estimate Equation 1.[38]

Marginal admission to these schools has effects that are very different from attending an IPN school, as shown in Table 10. Admitted students experience increases in mean peer COMIPEMS score, GPA, and parental education, although in each case these increases are only about half of those resulting from marginal IPN admission. Admission, on average, decreases students' commute slightly. In contrast with the IPN results, the estimated effect on dropout is small and negative. Estimated effects on ENLACE exam scores are close to zero and statistically insignificant for both math and Spanish. The dramatic difference in effects between IPN and high-cutoff nonelite schools suggests that particular features of IPN attendance—higher academic rigor and longer commutes, for example—drive their large admission effects.

F. Validity Checks

There is no a priori reason to think that the RD design might be invalid. Because the school-specific cutoff scores are determined in the process of the computerized assignment, monitored by school subsystem representatives and independent auditors, there is no opportunity for student scores to be manipulated in order to push particular students from marginal rejection to marginal admission. Nevertheless, Figure 8 provides graphical evidence of the design's validity, showing the distribution of centered COMIPEMS scores for students in the RD sample. Panel A shows the entire density, while Panel B zooms in on a smaller window around the cutoff. There is no visual evidence for a jump in the density of COMIPEMS score to one side of the cutoff or the other. We test formally for a discontinuous change in the density, following McCrary (2008). The p-value for this test is 0.90, in agreement with the visual evidence presented.

As further support for the RD design, we recall the balance of baseline covariates across the admission cutoff shown in Figure 5 and Table 6, Panel A. The lack of a discontinuity in these covariates suggests that students were unable to sort into or out of IPN admission, as we would expect given the computerized assignment process.

As with any study using a RD approach, there may be some skepticism in extrapolating the effects for marginal students to the rest of the sample. This would be a particular concern if there were few students near the margin compared to the total population of IPN students. The nature of the assignment mechanism, however, tends to bunch students near the cutoff of the school to which they are admitted, since a modestly higher score would often lead to admission to a more-preferred school. Similarly, many of the students admitted to the IPN subsystem are only a few points away from rejection and assignment to a non-IPN school. In fact, 34 percent of students admitted to an IPN school are within seven COMIPEMS points of falling out of the IPN subsystem, while more than half are within 12 points of the boundary. The standard

38. Note that we again confront the issue that some students in the sample score high enough that they are assigned to UNAM schools and thus have missing ENLACE data. We have checked the robustness of our results by dropping students who would be assigned to UNAM schools for various scores above the cutoff, and results do not change qualitatively.

Table 10
Regression Discontinuity Estimates of Effect of Admission to High-Cutoff non-IPN Schools on School Characteristics and Student Outcomes

Dependent Variable	Mean COMIPEMS Score (1)	Mean Middle School GPA (2)	Mean Parental Education (yrs.) (3)	Distance from Home to School (km) (4)	Dropout (Not Taking ENLACE Exam) (5)	ENLACE Math Score (6)	ENLACE Spanish Score (7)
Score ≥ cutoff	10.981***	0.168***	0.630***	–0.504**	–0.030**	0.014	–0.017
	(0.5814)	(0.0193)	(0.0486)	(0.2159)	(0.0135)	(0.0202)	(0.0241)
	[0.00]	[0.00]	[0.02]	[0.00]	[0.01]	[0.54]	[0.47]
Observations	18,130	21,652	18,130	30,075	43,266	24,498	25,966
Adjusted R-squared	0.677	0.788	0.681	0.060	0.096	0.141	0.106
Mean of dependent variable 1 point below cutoff	67.061	7.999	10.316	6.680	0.453	0.112	0.299
Bandwidth	5.1	5.6	5.4	8.8	11.5	13.4	14.1

Notes: Estimates are from local linear regressions, including piecewise-linear terms in COMIPEMS score and cutoff school-year fixed effects. The edge kernel is used in each regression and in computation of the corresponding optimal Imbens–Kalyanaraman bandwidth. Dependent variables in columns 1–3 are mean characteristics of all students admitted to the student's admitted school in his admission year. Standard errors clustered at the admitted high school level are in parentheses. Wild cluster bootstrapped p-values, clustered at the centered COMIPEMS score level, are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

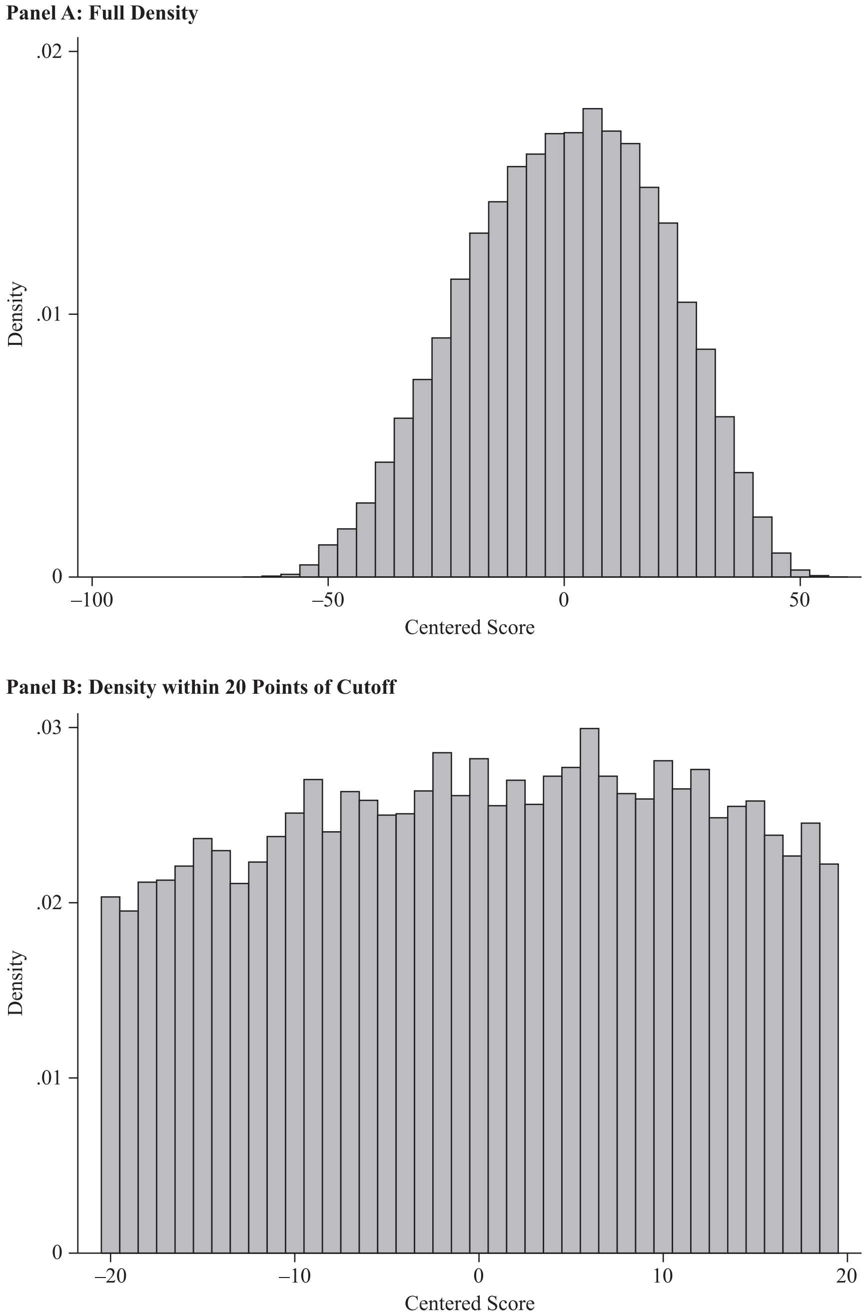


Figure 8

Density of Centered COMIPEMS Scores for Students in the Regression Discontinuity Sample

Notes: Panel B is a closer view of the centered score values near the cutoff, presented in order to see more clearly the density of scores close to the cutoff.

deviation of COMIPEMS score in the full sample is 17.95 and the within-school standard deviation for IPN students is 7.19, implying that a significant portion of IPN students are not far from the margin of the IPN subsystem.

VI. Discussion

This paper used Mexico City's high school allocation mechanism to identify the effects of admission to a subset of its elite public schools, relative to their nonelite counterparts. At least for marginally admitted students, elite schools present an important tradeoff. Elite admission appears to affect student math test scores positively, even under the conservative assumptions used to produce a lower bound for this effect. However, admission is found to significantly increase the probability of dropping out of school. Students with lower middle school GPAs are particularly adversely affected, suggesting that elite schools are too challenging for some students, and they either fail out or elect to leave school because of it. Mexico City's expansive geographical footprint, along with the relatively concentrated elite school locations, allow us to see how changes in commuting distance affect dropout. We find that commuting imposes a significant cost on students in terms of dropout probability.

Why do many students who are most likely to encounter a higher dropout probability due to elite admission—in particular those with lower GPAs and those who live far from elite schools—continue to choose elite schools? Even if students understand this tradeoff, they may value the expected academic gains or labor market advantage of an elite credential sufficiently that they are willing to bear the additional risk of dropping out. On the other hand, perhaps students do not realize that elite admission increases dropout risk. Dustan (2016) observes that when students witness an older sibling drop out, they are less likely to choose that school during the COMIPEMS application process compared to the case where the older sibling graduates. This suggests that there is incomplete information about school characteristics or student–school match quality. Bobba and Frisancho (2014) find that many students taking part in COMIPEMS have upward-biased beliefs about their own abilities, such that when they receive a signal about their ability, their choice portfolios shift away from elite schools. Thus, it may be that students know that elite admission increases dropout probability on average, but do not expect this to affect them personally. Students also may fail to anticipate other challenges associated with being a low performer at an elite school, such as social exclusion (see, for example, Pop-Eleches and Urquiola 2013; Weinberg 2007).

The existence of this tradeoff between academic benefit and dropout probability highlights an important educational policy issue in Mexico. As explained in Section II, transferring between subsystems is difficult, in part because accumulated credits do not necessarily transfer. The Comprehensive High School Education Reform (RIEMS) represents an attempt to rectify this by imposing a (partial) common curriculum, but this reform has faced delays and political opposition and its future remains in question.[39]

39. The component of this reform that addresses curricular harmonization is the Common Curricular Framework ("Marco Curricular Común" or "MCC"). The Secretariat of Public Education states, "A direct benefit of the MCC is that it will facilitate the creation of mechanisms to transfer between different schools and subsystems, which is an important advantage for students, who will be less likely to permanently abandon their studies" (Secretaría de Educación Media Superior 2008, p. 75).

Such rigidity in the current system may explain why the academic benefit-dropout tradeoff is so strong in this paper in comparison to studies in other countries. Our result highlights the value of flexibility in choice-based admissions systems, so that the consequences of a "bad" choice can be mitigated, provided that lateral transfers to more competitive schools are not allowed as a means of gaming the current system.

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