Winning admission to an elite school both promises rewards and imposes substantial risks on most students. We find that elite school admission in Mexico City raises end-of-high school test scores by an average of 0.12 standard deviations for the marginal admittee, without discernible heterogeneity with respect to student characteristics. However, it increases the risk of high school dropout by 7.7 percentage points. Students with weaker middle school grades and lower parental education experience a much larger increase in dropout probability as a result of admission. We show that the effect on exam scores is robust to accounting for dropout.

JEL Codes: O15, I20
Keywords: Elite schools, Academic achievement, School dropout
1. Benefits and Risks of Attending an Elite School

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, e.g., Hastings, Kane, and Staiger 2006). Attending a “better” school, as defined by peer ability or school resources, is usually thought to benefit students academically. For example, a better-funded school is able to afford more and better educational inputs. And a student may benefit from working with high-achieving and highly motivated peers. 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.¹ Students experiencing such challenges may fail to complete their education at all, which is probably a much less desirable outcome than graduating from a worse school.

This paper quantifies the trade-off between dropout risk and academic benefit facing students admitted to Mexico City’s elite public high schools. Mexico City is ideal for this exercise for two 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.

A simple regression discontinuity design, made possible by the assignment mechanism, is used to discover whether students experience a change in dropout probability or exam scores as a result of admission to an

¹ Duflo et al. (2011) elaborate on the potential benefits and drawbacks of ability tracking.
elite school, using their next most-preferred school that would admit them as
the counterfactual. There is a clear tradeoff for most marginally admitted
students. Admission to an elite school raises the probability of high school
dropout by 7.7 percentage points, compared to an average probability of 46%.
Along with this substantial increase in dropout probability, admission also
results in an average gain of 0.12 standard deviations on the 12th grade
standardized exam. Less-able students and those with less-educated parents
experience larger increase in dropout probability, but there is no evidence that
they experience a smaller boost in their exam scores from elite admission. We
introduce and carry out a procedure that estimates the exam score effect while
accounting for differential dropout with respect to observable and
unobservable characteristics, and confirm this positive effect.

While a structural treatment of student preferences is not the subject of
this paper, we also present reduced form evidence showing that students of
lower socioeconomic status (SES) and lower performance in middle school
choose elite schools less often, compared to neighboring high-SES or high-
performance students with the same entrance exam score.2 The paper’s main
findings offer one explanation for this result. Weak or disadvantaged students
may understand that elite school admission is a double-edged sword: while the
expected academic benefit for graduates is positive, the increased chance of
leaving high school without a diploma makes applying to an elite school a
risky choice.

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 admission on outcomes.
Clark (2010) finds little effect of admission to elite high schools in the United
Kingdom on exit exam scores four years later. Abdulkadiroglu et al. (2011)

2 The finding of differential application behavior with respect to SES is consistent with the
literature on under-matching in colleges in the United States, in particular Hoxby and Avery
(2012).
find that admission to competitive "exam schools" in Boston and New York has little effect on standardized achievement tests. Dobbie and Freyer (2011) also find that the New York elite schools do not have an appreciable effect on long-run outcomes such as SAT score or college graduation. In the context of developing and middle-income countries, 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. In a much different study, Duflo et al. (2011) randomly assigned Kenyan schools into a tracking regime where they divide 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 may 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.

The literature on the relationship between school quality and student dropout is sparser. Recent studies have mostly focused on the impacts of specific aspects of quality, randomly varying one aspect to see if it increased primary school participation, which differs from the concept of dropout in that reduced participation may not result in permanently abandoning schooling.

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3 Estrada and Gignoux (2011) 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.

while dropout usually does. For example, Glewwe, Ilias, and Kremer (2009) find no effect of a teacher incentive pay scheme on student participation in Kenya. 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 decreases dropout. This could be due to increased 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 2 gives a detailed overview of the Mexico City high school admissions system. Section 3 sets forth the methodology for identifying the effects of admission on outcomes. Section 4 describes the data and Section 5 gives the empirical results and several validity checks. Section 6 uses the results to rationalize revealed preference for elite schools. Section 7 concludes.

2. Mexico City public high school system and student enrollment mechanism

Beginning in 1996, the nine public high school systems 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 (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 Mexico City metropolitan area that addressed such inefficiencies and increased transparency in student admissions.

Any student wishing to enroll in a public high school 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 twenty high schools that they want to attend.\(^5\) 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 matters 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 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 system and independent auditors. The assignment process is as follows. First, each school system 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. Next, a computer program proceeds in descending order through the students, assigning each student to her highest-ranked school with seats remaining when her turn arrives. In some cases, multiple students with the same score have requested the final seats available in a particular school, such that the number of students outnumbers the number of seats. When this happens, the representatives in attendance from the respective school system must choose to either admit all of the tied applicants, exceeding the initial quota, or reject all of them, taking fewer students than the quota. If by the time a student’s turn arrives, all of her

\(^5\) 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.
selected schools are full, she must wait until after the selection process is complete and choose from the schools with open spots 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. 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 decisions offer a powerful avenue for strategically shaping a school's student body.  

At the end of the final year of high school (grade twelve), students who are currently enrolled take a national examination called the Evaluación Nacional de Logro Académico en Centros Escolares (Enlace), which tests students in Spanish and mathematics. This examination has no bearing on graduation or university admissions and the results have no fiscal or other consequence for high schools. It is a benchmark of student and school achievement and progress.

3. Regression discontinuity design and sample definition

The goal of this paper is to determine how much (marginal) admission to an elite school changes students’ probability of dropout and their end-of-high school exam scores. Put another way, the econometric challenge is to estimate the effect on academic outcomes from admission to a school in an elite system instead of admission to the student's next choice, provided that the next choice was not elite, holding constant Comipems score and all student characteristics, observed and unobserved.

The Comipems assignment mechanism permits a straightforward  

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6 The only obvious case would be to drastically underreport available seats at a school to reduce enrollment. But setting an artificially low seat quota and planning to accept students up to a level close to "true" capacity in the event of a tie either results in the school being under-enrolled (if there are too many tied students to accept) or enrolled near the level that would prevail with the true quota reported and all ties rejected.
strategy for identifying the causal effect of elite school admission on outcomes, through a sharp regression discontinuity (RD) design. Each school $S_j$ that is oversubscribed (i.e., with more demand than available seats) accepts all applicants at or above some cutoff Comipems exam score $C_j$, and rejects all applicants below $C_j$. Whether or not a student who wants to attend a particular school is actually admitted is determined entirely by whether or not she is above or below the cutoff score, giving a sharp discontinuity in the probability of admission (from 0 to 1) when the student reaches the cutoff. Considering one elite school at a time, the RD specification for school $S_j$ is:

$$Y_{ij} = g_j(c_i) + \delta_{ij} \text{admit}_{ij} + \epsilon_{ij}$$

where $g_j$ is a function of Comipems score $c_i$ (in practice, a separate linear term on either side of the cutoff), $\text{admit}_{ij}$ is equal to 1 if student $i$ was admitted to school $S_j$ and zero otherwise, and $Y_{ij}$ is either a dummy variable for student $i$ dropping out of school or a continuous variable for Enlace exam score. The sample consists only of students who would have liked to attend school $S_j$ when their turn for assignment arrived and have been barely admitted or rejected from the school. That is, they listed school $S_j$ as a preference and when their turn for assignment arrived, all schools listed above school $S_j$ had already been filled, and their Comipems score is close to $C_j$. Furthermore, the sample is restricted only to students who are at the margin of the elite system altogether, meaning that we exclude students close to the threshold of an elite school but who fall to another elite school upon rejection.

The concept of a student being close to a specific elite school’s admission threshold is key to the empirical analysis, so it is explained precisely here. The set of $M$ schools requested by a student (suppressing the $i$ subscript) is $S = \{S_1, S_2, \ldots, S_M\}$, where $S_1$ is the most preferred. Each school is characterized by its threshold $C_k$ and an indicator for whether it is elite ($E_k = 1$) or not ($E_k = 0$). According to the assignment rule, a student with score $c$ is admitted to school $S_j \in S$ if $j = \min \{k: c \geq C_k\}$. Let the bandwidth
used in estimation be \( b \) (e.g., 5 Comipems points). The group of students considered closely above elite school \( S_j \)'s threshold is the set of students such that:

1. The student was admitted to that school: \( S_j \in S, j = \min \{k: c \geq C_k\} \) and \( E_j = 1 \)
2. The student would be rejected if she lost \( b \) points: \( c - b < C_j \);
3. The school attended upon marginal rejection is not elite: \( E_r = 0 \) for \( S_r \in S \) and \( r = \min\{k: k > j, C_k < C_j\} \).

The group of students considered closely below elite school \( S_j \)'s threshold is the set of students such that:

1. The student was admitted to a non-elite school \( S_l \in S: l = \min \{k: c \geq C_k\} \) and \( E_l = 0 \);
2. The student is \( \bar{b} \leq b \) points below \( S_j \)'s threshold and the student prefers \( S_j \) over her current placement: \( c + \bar{b} = C_j, S_j \in S, \) and \( j < l \);
3. No other elite school would be attended if the student gained a quantity of points less than \( \bar{b} \):

\[
\{n: n < l, c < C_n \leq c + \bar{b}, E_n = 1\} = \emptyset
\]

Taken together, the "above" and "below" students form \( \text{Sample}_j \), the RD sample for elite school \( S_j \).\(^7\)

Returning to equation (1), we see that \( 1(c_i \geq C_j) \) is an instrument that perfectly predicts \( \text{admit}_{ij} \) for the students in \( \text{Sample}_j \). Provided that the control function \( g_j \) is specified correctly and is continuous at \( c_i = C_j, \) \( \delta_j \) gives the estimated local average treatment effect (LATE) of admission to elite school \( S_j \) compared to admission to those schools attended by rejected students (Imbens and Lemieux 2008).\(^8\)

\(^7\) This sample definition ensures that a student in the sample for \( S_j \) cannot belong to the sample constructed for any other elite school, although this is not necessary for consistent estimation (see, e.g., Pop-Eleches and Uquiola (2013)).

\(^8\) This is an intention-to-treat effect since students do not necessarily attend the school to which they were admitted. But in practice, compliance is almost perfect. Of those in the RD sample who take the 12th grade exam, 99.8% of the students rejected from the elite system.
There are many elite schools, so in order to give the average effect of elite school admission, equation (1) is estimated for each of the elite schools and \( \delta = \sum_{j \in J} \frac{N_j}{N} \delta_j \) is computed, where \( \{S_j, j \in J\} \) is the set of elite schools, and \( N_j \) and \( N = \sum_{j \in J} N_j \) are the number of students at the threshold of school \( S_j \) and the total number of students in the sample, respectively. In practice, we take the union of the disjoint school-specific samples \( \text{Sample}_j \), thus forming a sample of all students near the threshold of the elite system, estimate one regression with threshold fixed effects and slope and admission parameters that vary by threshold, clustering the standard errors by middle school attended, and then compute \( \delta \) and its standard error using the results:

\[
Y_{ij} = g_j(c_i) + \delta_j \text{admit}_{ij} + \mu_j + \epsilon_{ij} \quad \text{for } i \in \text{Sample}_j, j \in J
\]

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 school preferences. Even if students are choosing strategically or making mistakes in their selections, this behavior should 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.

4. Data description

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 take the exam in a non-elite school, while 96.1% of students admitted to the elite system take the exam in an elite school.
grade Enlace exams. The Comipems dataset includes all students who registered for the exam, with their complete ranked listing of up to twenty 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. The matching rate of Enlace takers to their Comipems scores is nearly 100% and will be discussed further in section 5.3.

The “elite” high schools being considered in the regression analysis are the group of 16 high schools affiliated with the Instituto Politécnico Nacional (IPN). For every seat available in an IPN school, 1.9 students list an IPN school as their first choice. Every IPN school is oversubscribed. Compared to

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9 The 2010 data is used in order to match students from the 2006 Comipems cohort who took four years to complete high school instead of three.
10 There is another elite high school system, affiliated with the Universidad Nacional Autónoma de México (UNAM). These schools do not give the Enlace exam, so they are excluded from the regression analysis. The IPN vs. non-elite student body comparison in this paragraph excludes the UNAM students. Students selecting an UNAM school as their first choice 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. We include a dummy variable for exam version in all regressions.
the non-elite schools, the IPN’s student body has higher Comipems exam scores (74.9 points vs. 58.7), grade point (8.24/10 vs. 7.98/10), parental education (10.7 years vs. 9.7), family income (4,634 pesos/month vs. 3,788), and Enlace exam score (0.52 normalized score vs. -0.12). While we do not have data on this point, it is widely accepted that IPN schools receive more funding on a per-student basis than non-elite schools.

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. Summary statistics for this sample and the subsample consisting only of students located at the threshold of IPN admission are in Table 1. Students near the admissions threshold to an IPN school (column 2) are substantially different from the full sample (column 1). They are more likely to be male, have more educated parents and higher incomes, better grades, and Comipems scores that are more than half a standard deviation above the sample mean. These students score 0.36 standard deviations above the full sample average on the Enlace exams. It is clear from Table 1 that many Comipems exam takers do not take the Enlace. We will present evidence in section 5.3 that this is almost entirely due to student dropout rather than some other feature of the data.

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11 The size of the window for being considered “at the threshold” is 5 points above or below the respective IPN school’s cutoff score. Changing the window size will of course have a small impact on the summary statistics, but the regression results are very robust to smaller or larger window sizes.

12 A further set of restrictions is placed on the sample in order to ensure comparability between the admitted and rejected students. First, IPN admitted students who would be admitted to an UNAM school directly below their admission threshold are excluded. Their rejected counterparts were admitted to an UNAM school, which did not give the Enlace exam. Second, IPN-admitted students who, upon rejection, would not have received a school assignment during the computer assignment process, are excluded. The corresponding set of rejected students who consequently did not receive a computerized assignment are also excluded. This is to eliminate the set of students who may have no intention of attending any non-elite public high school.

13 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.
5. Effects of elite school admission

This section uses the regression discontinuity strategy outlined in Section 3 to estimate the effect of marginal admission to an IPN school on the probability of dropping out of high school before graduation and, conditional on taking the Enlace exam, on the exam score obtained. Because we lack individual-level data on graduation, taking the Enlace exam is used as a proxy for graduation. Only students on track to graduate at the end of the school year are registered to take the exam. We present evidence in section 5.3 that this is a good proxy, in particular that schools do not strategically administer this exam. Thus the only sample used from this point onward is that of students at the threshold of an IPN school who would fall out of the IPN system if rejected. This corresponds to Column 2 of Table 1.

5.1 Probability of dropout

Marginal admission to an IPN school has a large, significant positive impact on the probability of dropout. Figure 1 illustrates this graphically, centering students’ scores about their school-specific cutoff score and plotting the dropout rate in a 5 point window around the threshold. Table 2 confirms this finding, reporting the average effect of admission on dropout estimated using the regression discontinuity design. Column 1, which excludes any additional covariates, estimates that the probability of dropping out increases by 7.72 percentage points, compared to the mean probability of 46.35%. Adding covariates—middle school GPA, parental education, family income, gender, hours studied per week in middle school, a normalized index of responses to questions about parental effort and involvement in schooling, and employment—in column 2 does not change this result importantly.

Column 3 adds interactions between the covariates and admission in order to explore whether the admission effect is heterogeneous with respect to student characteristics. The empirical specification is:

\[
\text{dropout}_{ijt} = \alpha_{jt} + \]
where $i$ indexes the student, $j$ indexes the threshold, $k$ indexes the covariates, and $x_k$ is the value of the covariate. In words, this specification has a threshold-year fixed effect, separate admission coefficients and linear trends in Comipems score (normalized as the difference from the cutoff score) for each elite school threshold, and for each covariate, a level effect, an interaction between the covariate and Comipems score that varies on either side of the threshold, and an interaction between the covariate and admission. The coefficients of interest are the $\theta_k$’s, which show whether the average effect of marginal admission is different for students with different levels of the covariate.

The effect of IPN admission on dropout is strongly heterogeneous with respect to middle school GPA. All else equal, students with lower GPAs experience a larger increase in probability of dropout. To interpret this differential effect, consider that the standard deviation of GPA in this sample is 0.74, the effect for a student with the mean GPA is 8.25 percentage points, and that $\hat{\theta}_{GPA}$ is -8.29. Then a student with a GPA one standard deviation below the mean experiences a $8.25 + (0.74 * -8.29) = 14.38$ percentage point effect of admission on dropout probability. Only students with very high GPAs, at the 88th percentile of the sample or above, are predicted to have a negative effect of admission on this probability. There is some evidence that the admission effect differs by SES as well. Students with higher levels of

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14 One might wonder if middle school GPA is a good proxy for student academic performance or if it could reflect characteristics of the middle school itself. To explore this possibility, we re-estimated the model while also including the mean GPA of the student’s middle school and its interactions as covariates. The results are basically unchanged: the coefficient on GPA changes from -16.85 to -16.56 and the coefficient on its interaction with admission changes from -8.29 to -8.74. It seems that GPA is a good proxy for academic performance, even across middle schools.
parental education are not affected as negatively by IPN admission. Students with parental education one standard deviation below the mean experience a $8.25 + (3.18 \times 1.33) = 12.48$ percentage point increase in dropout probability due to admission, while the effect is negative only for students with parental education in the 89th percentile of the sample or above. The results for other student characteristics are not statistically different from zero. One possible explanation for the significance of GPA and parental education, but not the other measures, is that these two are almost certainly the most accurately measured student characteristics. In particular, student-reported family income may be very inaccurate.

It is possible to predict for each student, on the basis of observables, the differential probability of dropout induced by admission simply by summing the $\hat{\theta}_k \times x_i^k$’s. Doing this, we find that 90% of students are predicted to have a higher chance of dropout due to IPN admission. This is not inconsistent with the IPN’s academic demands increasing the odds of school dropout for all admitted students. Rather, all students may want more strongly to stay in school if they are admitted to an elite school (causing a decrease in dropout probability), with the rigor of the IPN schools more than offsetting this impact for all but the best-prepared and most-supported students.

These results make clear that dropout is systematically related to IPN admission and its interaction with student characteristics. Specifically, 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 taking the Enlace have higher middle school GPAs and parental education. To show this, we estimate the following equation for each of the student characteristics $X_{it}$:

$$X_{it} = \alpha_{it} + \sum_j (\beta_{1j}(Comipems_{it}) + \beta_{2j}(Comipems_{it} \times admit_{ijt}) + \delta_j admit_{ijt}) + \varepsilon_{ijt}$$

If $X_{ijt}$ is balanced across the threshold, then $\delta_j$ should be close to zero. Table 3, Panel A gives estimates at the time of assignment (prior to dropout), where
we expect balance. Of the seven covariates tested, only hours studied per week is found to change discontinuously at the threshold. When estimating the equations jointly and performing a joint test for discontinuities, we fail to reject the null hypothesis of no discontinuity. Panel B, however, shows that within the sample of Enlace takers middle school GPA is unbalanced (about 1/7 S.D. higher for admitted students) as well as parental education (about 1/7 S.D. higher). This differential dropout, due entirely to the effect of IPN admission, may bias 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 use two methods to assess how severe this bias would have to be in order to push the point estimate of the admission effect, presented in the next section, to zero.

5.2 Enlace exam performance

We now turn to the effect of IPN admission on Enlace exam score. We first ignore the differential dropout issue raised in the previous section, and then propose ways to account for it in the next two subsections. Using all observed scores, Figure 2 suggests that there is a significant, positive effect of IPN admission on average score. Table 4 reports the regression discontinuity results for this relationship. Column 1, without covariates, gives a highly statistically significant admission effect of 0.12 standard deviations on the exam. Adding covariates in Column 2, the coefficient remains stable. Column 3 adds interactions between admission and the covariates, but we fail to reject that there are no differential impacts. Columns 4-6 suggest that this effect comes entirely from gains in math scores, between 0.21 and 0.23 standard deviations. The effect on Spanish scores, shown in columns 7-9, is indistinguishable from zero. This is perhaps unsurprising, given the IPN’s focus on math, science, and engineering.

5.2.1 Imputation from conditional quantiles
The first method for assessing the potential bias from dropout on the estimated exam score effect is to impute "penalized" scores to students who were induced to drop out either by admission to or rejection from an elite school. The idea behind this method is to assume that the rejected dropouts would have had better Enlace scores than their rejected, non-dropout peers with identical observable characteristics, and the admitted dropouts would have had worse scores than their observationally identical admitted non-dropout peers. The full procedure is explained in the Appendix. The intuition behind the procedure is given here.

We saw above that the probability to drop out of school was higher among the students marginally admitted to the elite schools than their marginally rejected counterparts. This effect of admission was estimated to be $\Delta = 7.72\%$ of the student body. Suppose for now that this effect is homogeneous and thus identical for all students. We can then classify the students in three groups: those who would never drop out regardless of admission, those who will always drop out, and those who are induced to drop out by admission. The concern is related to this third group because it is observed among the rejected but not among the admitted. By virtue of the discontinuity design, the shares of the three categories of students are identical on both sides of the threshold (after controlling for the function of Comipems score), and hence the share of induced dropouts is equal to $\Delta$, the difference in dropout rates among admitted and rejected. As we do not know which of the admitted dropouts are in this group, the idea is to impute a low grade to all of the admitted dropouts, but to weigh these observations with imputed scores by $\Delta/(\pi + \Delta)$, where $(\pi + \Delta)$ is the dropout rate among the admitted. This is equivalent to assigning an imputed score to a share $\Delta$ of the students only. There is no need to impute scores to the rejected dropouts since, under the assumption that admission only increases the probability of dropout, they would have dropped out if they had been admitted. This method thus avoids
imputing scores to the very large number of dropouts among the admitted and rejected whose behavior is unrelated to admission.

Next, we allow for some heterogeneity among students. The probability $\pi_i$ to drop out if rejected is specific to a student (we will use an estimated function of covariates and Comipems score $\pi(Comipems_i, X_i)$), as is the impact of admission on dropout $\Delta_i = \Delta(Comipems_i, X_i)$. We can then apply the rule described above for all individuals with $\Delta_i > 0$. In addition, there may be some students that will to the contrary drop out of school if they are rejected while staying in school if admitted. This is the group with $\Delta_i < 0$. For these students, the concern is the excess dropout among the rejected. We thus apply a high score to all of these rejected dropout students, and weigh the imputed score by $-\Delta_i/\pi_i$ where $\pi_i$ is their probability of dropout if rejected.

Which low score should be applied to each admitted dropout, and which high score should be applied to each rejected dropout? Recognizing student heterogeneity here as well, we use conditional quantile regressions to define high or low scores as observed among the non-dropouts with similar covariates and admission status.

We now summarize the method:

1. There are four groups of students: those who would never drop out regardless of admission, those who would always drop out, those who are induced to drop out by admission, and those who are induced to drop out by rejection.

2. Predict conditional dropout probability if rejected $\pi_i = \pi(Comipems_i, X_i)$ and impact of admission on dropout $\Delta_i = \Delta(Comipems_i, X_i)$ from equation (3) above.

3. Use conditional quantile regression to impute "low" Enlace scores ($m^{th}$ conditional quantile) for admitted dropouts with positive predicted differential dropout due to elite admission ($\Delta_i > 0$), and "high" scores ($1 - m^{th}$ conditional quantile) for rejected dropouts with negative predicted differential dropout due to elite admission ($\Delta_i < 0$):
4. Assign non-zero weights $\omega_i$ to dropouts with imputed Enlace scores according to the magnitude of their differential dropout, such that the weighted observations represent the sizes of the two groups that were induced to drop out as a result of admission or rejection. This is $\omega_i = \frac{\Delta_i}{(\Delta_i + \pi_i)}$ for admitted dropouts with $\Delta_i > 0$ and $\omega_i = -\frac{\Delta_i}{\pi_i}$ for rejected dropouts with $\Delta_i < 0$. Assign a weight of $\omega_i = 1$ to non-missing Enlace scores and $\omega_i = 0$ to those who dropped out but did not have higher predicted dropout probability due to their admission outcome. The result of this is a smooth density across the admissions threshold and balance of covariates across the threshold, as would be the case in a no-differential dropout scenario.

5. Perform the weighted Enlace score regression, including both the non-dropouts with their true scores and the dropouts with their imputed scores:

$$Enlace_{ijt} = g_j(Comipems_{it}) + \delta_j admit_{ij} + X'_{it}\beta + \mu_{jt} + \varepsilon_{ijt}$$

6. If the point estimate $\hat{\delta}_j$ is still positive, repeat the process while imputing a lower quantile for admitted students and a higher quantile for the rejected students. Stop when the point estimate is zero.

This procedure is performed for the overall Enlace score and the math score, but not for the Spanish score since the point estimate of the admission effect is negative. For the point estimate of the effect of admission on the overall score to be zero, students induced to drop out by admission would have to be on average in the 16th percentile of the conditional distribution of observed scores for admitted students with the same covariates, while at the same time the students induced to drop out by rejection would have to be in the 84th percentile of the conditional distribution of observed scores for rejected students. For math, these numbers would have to be more extreme, in the 5th
and 95\textsuperscript{th} percentiles, respectively.\textsuperscript{15} That is, differential dropout would have to be among students who are quite low-performing in comparison to non-dropout peers with the same observable characteristics and admissions outcomes. In particular, the effect on math scores appears very robust to the influence of dropout.

\textbf{5.2.2 Application of Altonji et al. (2005)}

Another approach to assessing the bias in the admission effect is to recognize that dropout creates an imbalance in both observables and unobservables between the admitted (treated) and rejected (untreated) groups. This insight allows one to apply the well-known method of Altonji et al. (2005), which informally assesses the severity of the bias by answering "how much worse would selection on unobservables have to be compared to the selection on observables in order for the treatment effect to be zero?" We refer the reader to the original paper for an in-depth discussion of the method. Here, we have applied their procedure directly except that we condition on Comipems score, estimating the equation:

\begin{equation}
Enlace_{ijt} = g_j(Comipems_{it}) + \delta_j \text{admit}_{ij} + X'_{it}\beta + \mu_{jt} + \epsilon_{ijt}
\end{equation}

where $g_j(Comipems_{it})$ is piecewise-linear, $\mu_{jt}$ are threshold-year fixed effects, and $X_{it}$ is the vector of covariates for which selection on observables is considered.

The results of this procedure suggest that the admission effect on the overall Enlace score is somewhat robust, while the effect on math scores is extremely robust. Selection on unobservables would have to be 1.80 times as strong as selection on observables to wipe out the positive point estimate on the overall score; for math, it would have to be 9.55 times as strong. Taken

\textsuperscript{15} The effect on overall Enlace score becomes insignificant at the 5\textsuperscript{th} level when the 38\textsuperscript{th} and 62\textsuperscript{nd} percentiles are imputed, respectively; there, the point estimate is 0.08. The effect on math scores becomes insignificant when the 15\textsuperscript{th} and 85\textsuperscript{th} percentiles are imputed, where the point estimate is 0.09.
together with the imputation results, there is good evidence for an overall admission effect and very strong evidence for a math effect.

5.3. Validity checks

Here we present three validity checks to address potential concerns with the results. First, support for the validity of the regression discontinuity design is given. Second, the insensitivity of the results to a wide variety of bandwidths is shown. Third, support is given for the assertion that the dropout-related results in this paper are indeed due to IPN students leaving school at a higher rate, rather than a data issue.

There is no a priori reason to think that the regression discontinuity design might be invalid. Because the school-specific cutoff scores are determined in the process of the computerized assignment process, monitored by school system 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 3 provides graphical evidence of the design's validity, showing the distribution of Comipems scores of students near each IPN school cutoff normalized by subtracting off the threshold-specific cutoff score. While the histogram is fairly coarse due to the discreteness of the score, there is no visual evidence for a jump in the density of Comipems score to one side of the cutoff or the other.16

There may be some concern about the density declining rapidly starting two points above the cutoff. The reason for this is that some IPN admittees have listed an UNAM high school (the other elite system) as above the IPN school on their preference list, and scoring several points above the IPN cutoff was sufficient for them to attend the UNAM school. In order to ensure that this is not biasing the RD results, all students who would attend an

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16 The test for a discontinuity in the density of the running variable, proposed by McCrary (2008), does not seem to apply well to the case where the running variable has few points of support. Still, this test fails to reject the null hypothesis of no discontinuity.
UNAM school upon scoring at least 2 points above their respective IPN cutoff are dropped. Panel B shows that this approach does not give rise to the declining density with higher scores. Re-estimating the dropout and Enlace regressions, results (not reported here) only change slightly: the estimated impact on dropout in Table 2, Column 3 rises from 8.25 percentage points to 8.82, while the estimated impact on Enlace score in Table 4, Column 3 rises from 0.12 to 0.15 standard deviations, both statistically significant at the 1% level. We note, however, that the estimated differential effect on dropout with respect to parental education declines from 1.33 to 0.82 and is no longer significant at the 10% level.

All reported results are highly robust to changing the bandwidth. Results from regressions using 2 through 10 point window sizes, not reported here, are very similar to those obtained with the 5-point window, although the standard errors for the 2-point window are quite large. Adding a cubic control function for the 10 point window regressions does not change the appreciably. Excluding the noisy 2-point window result, the dropout result for the un-interacted model with covariates (Table 3, column 2) varies from 7.10 to 8.25. The corresponding Enlace score result (Table 4, column 2) varies from 0.10 to 0.12 standard deviations. The differential dropout results with respect to covariates are noisy and insignificant for window sizes below 5, but the other bandwidths yield results very similar to those reported previously. Thus, for all key results, the estimates are highly insensitive to bandwidth choice.

Finally, there is substantial evidence that the difference in Enlace taking rate between students admitted to and rejected from the IPN is due to students dropping out of school, rather than a data problem or rate at which 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 admitted to the IPN in the full sample, 99% are matched successfully to their Comipems score. Another possibility that we can dismiss is that the IPN is selectively administering the
exam to its best 12th graders. Although the Enlace is taken at the end of the school year, schools must report the full roster of students in their final academic year to the Secretariat of Education so that all of those students can be programmed to take the exam. The ratio of actual exam takers to those programmed in the fall is nearly identical between the IPN and non-IPN schools (81%). Thus differential exam taking would have to be sufficiently premeditated to 1) fail to register low-ability students in the Fall and 2) systematically prevent the unregistered students from showing up at the exam. The exam is given by proctors from outside of the school. Administrators who run the Enlace express doubt that a school system would go through this trouble, especially when considering that Enlace scores are not used to allocate resources or to incentivize or punish educators. Finally, 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. The differential exam taking rate, then, cannot be explained by students taking longer to graduate in the IPN but not dropping out.

As with any study using a regression discontinuity approach, there may be some skepticism in extrapolating the effects for marginal students to the rest of the sample. 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 preferred school. In fact, 49% of students admitted to an IPN school are within 7 Comipems points of their school’s cutoff score. The standard deviation of Comipems score in the full sample is 17.95 and the within-school standard deviation for IPN students is 7.19, meaning that the bottom half of students in an IPN school’s score distribution is quite homogeneous in terms of both absolute score and within-school relative score. Thus the estimated impacts can be thought of as applying, at least, to a significant portion of the IPN population.
6. Preference for the elite schools

Students with lower GPAs and those from families with lower parental education are less likely to apply to elite schools. The findings in this paper offer one way of rationalizing this empirical regularity. Students from such backgrounds face a less desirable dropout risk-academic reward tradeoff and may respond rationally by choosing to avoid it altogether. This should be particularly true for students who are likely to gain admission to an elite school only at the margin.

To show that conditional on Comipems score, children of more-educated parents are more likely to list an elite school as their first choice, the following local linear regressions are estimated for all observations within a 2-point bandwidth of each Comipems point value $c$:

$$
 elite_{int} = a_{mtc} + \beta_c Comipems_i + \theta_{e} educ_i + \epsilon_{imtc},
$$

where $elite_{int}$ is a dummy variable equal to 1 if student $i$ in year $t$ from municipality/delegation $m$ chose an elite school as her first choice, and $educ_i$ is years of parental education.$^{17}$ The municipality/delegation of residence of the student is added to control for the possible unequal geographic access to elite schools. The parameters of interest are the $\theta_c$'s, which measure the marginal effect (though not a causal relationship) of parental education on elite school preference only for students with $Comipems_i$ near $c$. Figure 4, Panel A graphs these coefficients and shows that for all values of Comipems score above 70 points, i.e., that are high enough to gain admission to the least-competitive elite school, higher parental education is correlated with higher rates of elite school preference. For example, at a score of 80 points, moving parental education from elementary school graduate to bachelor's degree is associated with an increase in the probability of choosing an elite school of 15

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$^{17}$ Recall that both IPN and UNAM schools are included in the set of elite schools. Here we can include the UNAM schools in the analysis because no Enlace exam scores are required.
percentage points (over a base rate of 60% for elementary graduates). As expected, this disparity falls for students with higher Comipems scores, as these students are less likely to find themselves at the bottom of the score distribution in their elite school. Panel B graphs the coefficient from equation (6) when parental education is replaced with GPA. At a Comipems score of 80, students with a 9.0 GPA are 15 percentage points more likely to select an elite school than those with a 7.0 GPA. These are large differences, indicating that among students living in the same municipality or delegation and with the same possibility of admission to elite schools as a result of their Comipems score, those of lower SES or GPA are much less likely to list one elite school as a first choice. The less favorable risk-reward tradeoff facing these students offers one way to explain this result.

7. Discussion

This paper has 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 non-elite counterparts. At least for marginally admitted students, elite schools present an important tradeoff. Admission is found to positively affect student test scores, increasing end-of-high school exam scores by 0.12 standard deviations under the assumption that dropout does not induce bias. Allowing for bias due to dropout lowers this estimate, but severe assumptions about the importance of this bias are required to negate the positive effect. At the same time, elite admission increases the probability of dropout for the vast majority of marginally admitted students (90% have a positive effect of admission on dropout), by 7.7 percentage points on average. The fact that this tradeoff is, in expectation, worse for those from less advantaged family and academic backgrounds offers one possible explanation for the lower rate at which qualified students of low SES or GPA apply to elite

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18 The estimated education effect is lower for scores near 65 because few students with those scores attend an elite school. Similarly for scores over 100 because almost all students with those scores do attend.
high schools.

Existence of this tradeoff between graduation probability and academic benefit highlights an important educational policy issue in Mexico. The current configuration of the high school education system does not facilitate lateral transfers of students between school systems, which are run by numerous entities at the local, state, and national level. Students who find that their current school is a bad fit cannot easily switch to a school that balances academic rigor, curriculum, and other characteristics to their taste, unless they drop out of school entirely and attempt to begin elsewhere with zero credits. The recently begun Comprehensive High School Education Reform (RIEMS) represents an attempt to rectify this by imposing a (partial) common curriculum. Such rigidity in the current system may explain why the academic benefit-completion 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.

References


Appendix: Method for assessing bias induced by differential dropout

In this appendix, we set forth a method for assessing the bias due to
differential dropout induced by admission to an elite school, accounting for
the heterogeneity of this dropout effect in the population of students. This
procedure is in the spirit of previous bias-assessment and bias-bounding
procedures and has some methodological similarities, but there are key
differences. Lee (2005) trims the upper or lower part of the outcome
distribution for treated (or untreated) observations, leading to sharp upper and
lower bounds on the estimated treatment effect. When dropout from the
sample is substantial, as it is here, these bounds can be wide. Still, Lee’s
approach leads to tighter bounds than worst-case bounds such as in Horowitz
and Manski (1995). We take a less conservative approach that allows us to see
how bad the bias must be in order to find a point estimate of zero effect, rather
than assuming extreme outcomes for dropouts and then seeing if the resulting
bounds contain zero or not. This is more in the spirit of Altonji et al. (2005),
although our focus is on addressing dropout through imputation of outcomes
rather than making assumptions about the correlation between error terms in
the treatment and outcome equations for students with observed outcomes.

A1. Basic setup

To understand why dropout (not taking the Enlace exam) may induce
bias in the estimated effect of admission on Enlace score, first consider the
case of one elite school with randomly assigned admission, where there are no
covariates. There are two stages, one where it is determined whether the
student drops out \( (\text{drop}_i = 1) \) and then the stage where Enlace score is
observed for those who do not drop out:
\[
\text{drop}_i = \begin{cases} 
1 & \text{if } \text{drop}_i = \pi + \Delta \text{admit}_i + \nu_i > 0 \\
0 & \text{otherwise} 
\end{cases}
\]

\[
\text{Enlace}_i = \begin{cases} 
\alpha + \delta \text{admit}_i + \varepsilon_i & \text{if drop}_i = 0 \\
- & \text{if drop}_i = 1 
\end{cases}
\]

where \(\pi\) is the dropout rate among rejected students, \(\Delta\) is the effect of elite admission on dropout probability, \(\delta\) is the effect of elite admission on Enlace score, and \(\nu_i\) and \(\varepsilon_i\) are error terms. The problem is that if \(E[\nu|\text{admit}] \neq 0\) and \(\text{cor}(\varepsilon,\nu) \neq 0\), then the estimated effect of admission on score (\(\hat{\delta}\)) will be biased. The following procedure will make no assumptions about \(E[\nu|\text{admit}]\) or \(\text{cor}(\varepsilon,\nu)\), but rather see how severe the effects of differential dropout must be, in particular how poorly (or how well) the rejection- or admission-induced dropouts must do compared to the Enlace takers, in order to attribute the entire treatment effect to this bias.

We begin by imposing a monotonicity assumption: admission may not increase the probability of taking for some students and decrease it for others. This is satisfied by assuming a homogeneous treatment effect of \(\text{admit}_i\) on \(\text{drop}_i^*\), as in the setup above.

A2. Decomposition of mean score

First, suppose that admission increases the probability of dropout, so \(\Delta > 0\). The hypothetical average Enlace score, regardless of whether the exam is actually taken, is decomposed separately for rejected and admitted groups as follows:

\[
\overline{\text{Enlace}}^R = \frac{1}{n_1^R} \sum_{i: \nu_i < -\pi - \Delta} \text{Enlace}_i + \frac{1}{n_2^R} \sum_{i: \nu_i < -\pi} \text{Enlace}_i + \frac{1}{n_3^R} \sum_{i: \nu_i > -\pi} \text{Enlace}_i
\]
where $n_1^R$ is the number of students who were rejected from the elite school and would take the exam regardless of admissions outcome, $n_2^R$ is the number of rejected students who take the exam when rejected but would not when admitted, $n_3^R$ is the number of rejected students who did not take the exam (and would not have if admitted), and $n_1^A$, $n_2^A$, and $n_3^A$ indicate the number of students in the corresponding groups for those students who are admitted to the elite school.

The first sum in each group is the set of students who take the exam regardless of admission status, so their scores are always observed. The final sum is over students who never take the exam, so their scores are never observed. The middle sum is the set of students who take the exam if rejected but not if they are admitted. This is analogous to the "compliers" in an IV design, where compliance is dropping out and having no score observed. The bias in $\delta$ comes from including the scores of compliers in the rejected group but not in the admitted group.

Of course, the set of compliers in the admitted and rejected groups is unknown, but under randomization its size is not. How big is the set of missing compliers in the admitted group? To answer this, consider the following expressions for the count of observed exam scores as a proportion of all students in the group:

$$\frac{N_{obs}^R}{N^R} = \frac{n_1^R}{N^R} + \frac{n_2^R}{N^R} = 1 - \pi$$

$$\frac{N_{obs}^A}{N^A} = \frac{n_1^A}{N^A} = 1 - (\pi + \Delta)$$
A3. Defining weights for dropouts

Because of randomized admission, we know that
\[ \frac{n_A^R}{N^R} = \frac{n_A^D}{N^A} \] and
\[ \frac{n_R^D}{N^R} = \frac{n_R^A}{N^A}. \] It follows that
\[ \frac{n_A^D}{N^A} = \Delta, \] meaning that we are "missing" \( n_2^A = \Delta N^A \) compliers in the admitted group. The goal of this procedure is to add these "missing" admitted dropouts back into the sample with increasingly low imputed scores until their addition causes the estimated admission effect to be zero. We will do this by weighting the imputed scores of all \( N^A - n_1^A \) dropouts such that the equivalent of \( n_2^A \) of them are added. The proper weight is given by:

\[ \omega_i = \frac{n_2^A}{(N^A - n_1^A)} = \frac{\Delta}{(\pi + \Delta)} \]

This weight can be estimated easily, as \( \Delta \) and \( \pi \) are estimated in the dropout prediction equation. All admitted and rejected students who took the exam have \( \omega_i = 1 \) and all admitted students without a test score have \( \omega_i = 0. \)

If \( \Delta < 0 \), then the result is derived in the same way, and \( \omega_i = \frac{-\Delta}{\pi} \) is applied for dropouts in the rejected group and \( \omega_i = 0 \) for dropouts in the admitted group.

A4. Imputing scores for the missing observations

Imputation of scores for the admitted students can be done by quantile regression. In the simple case of randomization with no covariates, the equation for this is:

\[ \text{Enlace}_i = Q_m(\text{Enlace} | \text{admit}_i = 1) \]

where \( Q_m \) is the quantile function giving the \( m^{th} \) quantile of the observed score distribution among the admitted students. If the imputation is for

\[ ^{19} \text{Of course all of the weights can be normalized so that they sum to 1 by defining } \omega_i^* = \omega_i / \sum_j \omega_j. \]
rejected students, the conditional quantile is taken among the rejected students.
A5. Estimating the admission effect on scores including imputed observations

Estimation of the admission effect proceeds as it would without the imputed observations, with two obvious differences: the imputed observations are included and the observations are weighted. If the resulting $\hat{\delta}$ is still positive, then the conditional quantile is decreased (or increased, if the imputation is for rejected students) and the exercise is carried out again until the selected quantile is sufficiently low (high) that the admission effect is zero.

A6. Adding covariates

We have seen that the predicted probability of dropout depends on covariates, and that the effect of admission on dropout also depends on covariates. In fact, the predicted effect of admission on dropout is negative for some students and positive for others. Here the procedure is extended to allow for covariates, so the dropout equation is redefined as:

$$
\begin{align*}
drop_{i}^* & = \begin{cases} 
1 & \text{if } drop_i^* = \bar{\pi} + \tilde{\Delta}admit_i + X_i\gamma + (X_i \times admit_i)\theta + \nu_i > 0 \\
0 & \text{otherwise}
\end{cases}
\end{align*}
$$

The randomization assumption is retained, while the monotonicity assumption is relaxed slightly: conditional on covariates $X_i$, admission may not increase the probability of taking for some students and decrease it for others. Again, this is satisfied if we assume a treatment effect that is homogeneous conditional on observables, as presented in the equation above.

For notational convenience, define $\pi_i \equiv \bar{\pi} + X_i\gamma$ as the predicted probability of dropout if the student is rejected, conditional on covariates. Also define $\Delta_i \equiv \Delta + X_i\theta$ as the change in dropout probability due to admission for a student with covariate values $X_i$. 

The decomposition of mean Enlace scores is almost identical to the no-covariate case, except that the admission effect $\Delta$ is replaced by $\Delta_i$ and the baseline dropout $\pi$ is replaced by $\pi_i$. Now there are some observations with $\Delta_i > 0$ and some with $\Delta_i < 0$:

$$
\overline{\text{Enlace}}^R = 1(\Delta_i > 0) \left[ \frac{1}{n_1^R} \sum_{i: v_i < -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_2^R} \sum_{i: v_i > -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_3^R} \sum_{i: v_i > -\pi_i, v_i > -\pi_i - \Delta_i} \text{Enlace}_i \right] \\
+ 1(\Delta_i < 0) \left[ \frac{1}{n_1^R} \sum_{i: v_i < -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_2^R} \sum_{i: v_i > -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_3^R} \sum_{i: v_i > -\pi_i, v_i > -\pi_i - \Delta_i} \text{Enlace}_i \right]
$$

$$
\overline{\text{Enlace}}^A = 1(\Delta_i > 0) \left[ \frac{1}{n_1^A} \sum_{i: v_i < -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_2^A} \sum_{i: v_i > -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_3^A} \sum_{i: v_i > -\pi_i, v_i > -\pi_i - \Delta_i} \text{Enlace}_i \right] \\
+ 1(\Delta_i < 0) \left[ \frac{1}{n_1^A} \sum_{i: v_i < -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_2^A} \sum_{i: v_i > -\pi_i, v_i < -\pi_i - \Delta_i} \text{Enlace}_i + \frac{1}{n_3^A} \sum_{i: v_i > -\pi_i, v_i > -\pi_i - \Delta_i} \text{Enlace}_i \right]
$$

The unobserved sets of students for which scores need to be imputed are indicated in bold. By the same derivation as the no-covariate case but with the covariates and their interactions included, we derive the following set of weights:

1. Admitted, dropped out, $\Delta_i > 0$ (increased dropout probability due to admission): $\omega_i = \frac{\Delta_i}{\pi_i + \Delta_i}$
2. Rejected, dropped out, $\Delta_i < 0$ (increased dropout chance due to rejection): $\omega_i = \frac{-\Delta_i}{\pi_i}$
3. Did not drop out: $\omega_i = 1$
4. Otherwise: $\omega_i = 0$

This is the same as the no-covariate case except that it allows students in both the rejected and admitted groups to be weighted up, depending on the sign of the conditional differential dropout probability $\Delta_i$.

The rest of the process is the same as the no-covariate case but with one change: imputation is done via quantile regression, now conditional on the full set of covariates $X_i$, but imputing a low quantile for the admitted students and a high quantile for the rejected students. Here, we impute the $m$th conditional quantile for the admitted students and $1 - m$th conditional quantile for the rejected students:

$$Enlace_i = \begin{cases} Q_m(Enlace|X_i, admit_i = 1) & \text{if } \Delta_i > 0, admit_i = 1, \text{and } drop_i = 1 \\ Q_{1-m}(Enlace|X_i, admit_i = 0) & \text{if } \Delta_i < 0, admit_i = 0, \text{and } drop_i = 1 \end{cases}$$

A7. For which set of students is the admission effect estimated?

If differential dropout were only predicted to be positive for admitted students, then the imputation exercise would allow us to estimate the (penalized) admission effect for the group of students who do not drop out if rejected (regardless of whether they drop out if admitted). But here we have both students who are more likely to drop out when admitted and students who are more likely to drop out when they are rejected. So this exercise is performed for the group of students who are not "always-quitters" – students for whom admission and/or rejection would lead to taking the Enlace. This is not a commonly-used group in the treatment effects literature, but it has some appeal. It can be thought of as the whole group of students for whom we can conceive of comparing outcomes between groups of schools – we should never compare on the basis of students who will always drop out, but we may
indeed want to include in the comparison students who drop out in one group of schools but not the other, as well as those who always stay in school.

**A8. Extension to regression discontinuity**

The previous sections assumed randomization into treatment. To apply the same procedure to regression discontinuity, we use the assumption that in a sufficiently small window about the threshold, treatment is as good as randomly assigned conditional on a properly-specified function of the running variable (Imbens and Lemieux 2008). Thus we can simply include a function of Comipems score (normalized to zero at the cutoff score) in the dropout equation and in the Enlace score equation. We also include interactions between the de-meaned covariates and Comipems score, to allow the possibility that the covariates' influence varies with Comipems score:

\[
\text{drop}_i = \bar{\pi} + \Delta \text{admit}_i + \beta_1 \text{Comipems}_i + \beta_2 (\text{Comipems}_i \times \text{admit}_i) + X_i \gamma \\
+ (X_i \times \text{admit}_i) \theta + (X_i \times \text{Comipems}_i) \phi_i \\
+ (X_i \times \text{Comipems}_i \times \text{admit}_i) \phi_2 + \nu_i
\]

The rest of the procedure is the same, since \( \Delta_i \equiv \tilde{\Delta} + X_i \theta \) is still the difference in Enlace taking probability due to admission. The predicted probability of dropout given rejection, \( p_i \), can be estimated in the same way as before, but including the \textit{Comipems} terms; likewise for the imputation of the conditional quantiles.
Table 1. Characteristics of students eligible for assignment

<table>
<thead>
<tr>
<th></th>
<th>All students</th>
<th>Students at an IPN threshold</th>
<th>p-value for equality of (1) and (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>0.46</td>
<td>0.60</td>
<td>0.00</td>
</tr>
<tr>
<td>Maximum of mother's and father's education</td>
<td>10.18</td>
<td>10.61</td>
<td>0.00</td>
</tr>
<tr>
<td>Family income (thousand pesos/month)&lt;sup&gt;a&lt;/sup&gt;</td>
<td>4.22</td>
<td>4.49</td>
<td>0.00</td>
</tr>
<tr>
<td>Hours studied per week</td>
<td>5.19</td>
<td>5.52</td>
<td>0.00</td>
</tr>
<tr>
<td>Index of parental effort&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.00</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Student is employed</td>
<td>0.04</td>
<td>0.04</td>
<td>0.39</td>
</tr>
<tr>
<td>Middle school grade point average (of 10)</td>
<td>8.10</td>
<td>8.26</td>
<td>0.00</td>
</tr>
<tr>
<td>Number of schools ranked</td>
<td>9.31</td>
<td>10.49</td>
<td>0.00</td>
</tr>
<tr>
<td>Elite school as first choice</td>
<td>0.64</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Comipems examination score</td>
<td>63.74</td>
<td>73.55</td>
<td>0.00</td>
</tr>
<tr>
<td>Dropped out (only for students assigned to a non-UNAM school)</td>
<td>0.50</td>
<td>0.46</td>
<td>0.00</td>
</tr>
<tr>
<td>Enlace examination score (for those who took the exam)&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.01</td>
<td>0.35</td>
<td>0.00</td>
</tr>
<tr>
<td>Observations</td>
<td>354,581</td>
<td>8,244</td>
<td></td>
</tr>
</tbody>
</table>

Note. Standard deviations in parentheses.

<sup>a</sup> Average 2005-2006 exchange rate was 10.9 pesos/dollar.

<sup>b</sup> 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.

<sup>c</sup> 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.
Table 2. Regression discontinuity estimates of effect of IPN admission on dropout

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admitted to IPN</td>
<td>7.72***</td>
<td>8.12***</td>
<td>8.25***</td>
</tr>
<tr>
<td></td>
<td>(2.19)</td>
<td>(2.23)</td>
<td>(2.23)</td>
</tr>
<tr>
<td>Middle school GPA (of 10)</td>
<td>-20.33***</td>
<td>-16.85***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.86)</td>
<td>(2.59)</td>
<td></td>
</tr>
<tr>
<td>Parental education (years)</td>
<td>-0.56***</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.62)</td>
<td></td>
</tr>
<tr>
<td>Family income (thousand pesos/mo)</td>
<td>-0.21</td>
<td>-0.66</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.61)</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>-1.54</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.27)</td>
<td>(4.12)</td>
<td></td>
</tr>
<tr>
<td>Hours studied per week</td>
<td>-0.10</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.60)</td>
<td></td>
</tr>
<tr>
<td>Parental effort index</td>
<td>-0.52</td>
<td>-1.67</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
<td>(1.99)</td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>7.45***</td>
<td>7.68</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.87)</td>
<td>(8.48)</td>
<td></td>
</tr>
<tr>
<td>Middle school GPA * Admitted</td>
<td>-8.29***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.15)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental education * Admitted</td>
<td>-1.33*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.79)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family income * Admitted</td>
<td>0.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male * Admitted</td>
<td>-0.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hours studied per week * Admitted</td>
<td>-0.04</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.74)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental effort index * Admitted</td>
<td>0.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.53)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed * Admitted</td>
<td>2.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.74)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Threshold-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>8,244</td>
<td>6,978</td>
<td>6,978</td>
</tr>
<tr>
<td>R²</td>
<td>0.029</td>
<td>0.117</td>
<td>0.124</td>
</tr>
<tr>
<td>Mean of dependent variable</td>
<td>46.35</td>
<td>45.93</td>
<td>45.93</td>
</tr>
</tbody>
</table>

Note. Dependent variable is dropout*100.
All regressions include threshold-specific coefficients for Comipems score and (Comipems score * admitted), and a dummy variable for whether the UNAM exam was taken. Column (3) includes coefficients for (Comipems score * covariate) and (Comipems score * covariate * admitted) for each of the covariates.
Each of the covariates is de-meaned.
Robust standard errors, clustered at middle school level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.01
Table 3. Balance of covariates at time of assignment and at end of high school

Panel A. At time of assignment

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Middle school GPA (of 10)</th>
<th>Parental education (years)</th>
<th>Family income (thousand pesos/mo)</th>
<th>Male</th>
<th>Hours studied per week</th>
<th>Parental effort index</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admitted to IPN</td>
<td>-0.01</td>
<td>0.17</td>
<td>-0.10</td>
<td>-0.02</td>
<td>0.29*</td>
<td>-0.01</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.14)</td>
<td>(0.14)</td>
<td>(0.02)</td>
<td>(0.15)</td>
<td>(0.04)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Threshold fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>8,232</td>
<td>7,458</td>
<td>7,364</td>
<td>8,244</td>
<td>7,447</td>
<td>7,502</td>
<td>7,236</td>
</tr>
<tr>
<td>R²</td>
<td>0.06</td>
<td>0.02</td>
<td>0.02</td>
<td>0.09</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Mean of dependent variable</td>
<td>8.26</td>
<td>10.61</td>
<td>4.49</td>
<td>0.60</td>
<td>5.52</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>S.D. of dependent variable</td>
<td>0.74</td>
<td>3.16</td>
<td>3.18</td>
<td>0.49</td>
<td>3.25</td>
<td>0.95</td>
<td>0.20</td>
</tr>
<tr>
<td>p-value, joint significance of admission coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.19</td>
</tr>
</tbody>
</table>

Panel B. At end of high school

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Middle school GPA (of 10)</th>
<th>Parental education (years)</th>
<th>Family income (thousand pesos/mo)</th>
<th>Male</th>
<th>Hours studied per week</th>
<th>Parental effort index</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admitted to IPN</td>
<td>0.10***</td>
<td>0.43**</td>
<td>-0.01</td>
<td>-0.03</td>
<td>0.31</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.20)</td>
<td>(0.19)</td>
<td>(0.03)</td>
<td>(0.21)</td>
<td>(0.06)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Threshold fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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</tr>
<tr>
<td>Observations</td>
<td>4,419</td>
<td>4,024</td>
<td>3,979</td>
<td>4,423</td>
<td>4,013</td>
<td>4,045</td>
<td>3,895</td>
</tr>
<tr>
<td>R²</td>
<td>0.07</td>
<td>0.04</td>
<td>0.03</td>
<td>0.10</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Mean of dependent variable</td>
<td>8.47</td>
<td>10.69</td>
<td>4.52</td>
<td>0.56</td>
<td>5.68</td>
<td>0.10</td>
<td>0.03</td>
</tr>
<tr>
<td>S.D. of dependent variable</td>
<td>0.73</td>
<td>3.16</td>
<td>3.14</td>
<td>0.50</td>
<td>3.29</td>
<td>0.94</td>
<td>0.18</td>
</tr>
<tr>
<td>p-value, joint significance of admission coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.04</td>
</tr>
</tbody>
</table>

Note. All regressions include threshold-specific coefficients for Comipems score and (Comipems score * admitted), and a dummy variable for whether the UNAM exam was taken.

Robust standard errors, clustered at middle school level, in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

a p-value is from chi-square test of joint equality to zero of "Admitted to IPN" coefficients in columns 1-7. The equations are jointly estimated with seemingly unrelated regression.
<table>
<thead>
<tr>
<th></th>
<th>Enlace score (Math and Spanish)</th>
<th>Math score</th>
<th>Spanish score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Admitted to IPN</td>
<td>0.12***</td>
<td>0.11***</td>
<td>0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Middle school GPA</td>
<td>0.12***</td>
<td>0.18***</td>
<td>0.14***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Parental education (years)</td>
<td>-0.00</td>
<td>-0.01</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Family income (1000 pesos/mo)</td>
<td>-0.01*</td>
<td>-0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Male</td>
<td>0.01</td>
<td>0.13</td>
<td>0.26***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.08)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Hours studied per week</td>
<td>0.01**</td>
<td>0.02</td>
<td>0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Parental effort index</td>
<td>-0.04***</td>
<td>-0.02</td>
<td>-0.05***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Employed</td>
<td>-0.11*</td>
<td>-0.01</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.17)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Parental education * Admitted</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Family income * Admitted</td>
<td>-0.00</td>
<td>-0.01</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Male * Admitted</td>
<td>-0.10</td>
<td>-0.06</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.11)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Hours studied per week * Admitted</td>
<td>-0.01</td>
<td>-0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Parental effort index * Admitted</td>
<td>0.02</td>
<td>0.04</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Employed * Admitted</td>
<td>-0.11</td>
<td>-0.01</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.29)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>Threshold-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4,423</td>
<td>3,773</td>
<td>4,423</td>
</tr>
<tr>
<td>R²</td>
<td>0.21</td>
<td>0.22</td>
<td>0.18</td>
</tr>
<tr>
<td>Mean of dependent variable</td>
<td>0.35</td>
<td>0.36</td>
<td>0.36</td>
</tr>
</tbody>
</table>

Note. Dependent variable is Enlace score.
All regressions include threshold-specific coefficients for Comipems score and (Comipems score * admitted), and a dummy variable for whether the UNAM exam was taken. Columns (3), (6), and (9) include coefficients for (Comipems score * covariate) and (Comipems score * covariate * admitted) for each covariate.
Each of the covariates is de-meaned.
Robust standard errors, clustered at middle school level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Figure 1. Dropout rate for students near IPN system cutoff

Note. Scatterplot is of mean dropout rate vs. centered Comipems score, where dropout has been demeaned by regressing dropout on a set of threshold-year fixed effects and using the residuals. Lines represent a separate linear fit on each side of the admissions threshold. Gray region is a 95% confidence interval.

Figure 2. Enlace performance for students near IPN system cutoff

Note. Scatterplot is of mean Enlace score vs. centered Comipems score, where Enlace score has been demeaned by regressing Enlace score on a set of threshold-year fixed effects and using the residuals. Lines represent a separate linear fit on each side of the admissions threshold. Gray region is a 95% confidence interval.
Figure 3. Density of student scores around IPN system cutoffs

Panel A. Regular sample

Panel B. Sample without students who would attend an UNAM school if they had a centered Comipems score of 4

Note. Histograms show the density of centered Comipems score for different regression discontinuity samples. Panel A represents the full RD sample in table 1, column 2. Panel B represents the same sample except that it excludes any student who would attend an UNAM school if she had a centered score of 4.
Figure 4. Partial correlation of student characteristics with elite school first-choice preference

Panel A. Years of education

Note. Solid line is a smoothed line through the $\theta_c$ coefficients from estimating equation (6): $elite_{imt} = \alpha_{mtc} + \beta_c Comipems_i + \theta_c X_i + \varepsilon_{imtc}$, where $elite_{imt}$ is a dummy variable equal to 1 if student $i$ in year $t$ from municipality/delegation $m$ chose an elite school as her first choice, and $X_i$ is years of parental education (Panel A) or middle school GPA (Panel B). The lines represent the partial correlation between $X_i$ and elite school preference for different Comipems score values. Dotted lines are the 95% confidence intervals for the estimated $\theta_c$'s.