The Benefits and Hazards of Elite High School Admission: Academic Opportunity and Dropout Risk in Mexico City

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Mexico City uses a competitive admissions process to allocate students among its public high schools. Among these are school systems with a reputation as elite institutions with perceived quality far surpassing the other systems. This paper exploits the allocation mechanism to estimate the effects of admission to elite schools in comparison to other public schools. Marginal admission to the subset of elite schools examined increases the predicted probability of dropout by 8.5 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. On the other hand, marginal admission to an elite school raises end-of-high school test scores by an average of 0.12 standard deviations, without discernible heterogeneity with respect to student characteristics. The increased dropout risk for weaker students and those of lower socioeconomic status, together with the lack of evidence that the academic benefits accrue differentially to these students, offers one explanation for the finding that middle school performance and socioeconomic status positively predict elite school preference even among students with identical entrance exam scores.

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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, leaving them without a diploma. Failing out of a better school 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

[1] Duflo et al. (2011) elaborate on the potential benefits and drawbacks of ability tracking.

mechanism, is used to discover whether students experience a change in dropout probability or exam scores as a result of admission to an 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: those who score barely high enough on the entrance exam to attend an elite school and survive until the end of high school experience an average gain of 0.12 standard deviations on their 12th grade exam, but elite admission also raises the probability of attrition from high school substantially. The average marginally admitted student experiences an 8.5 percentage point decline in probability of taking the 12th grade exam, compared to an average probability of 54%. Poorer and less-able students experience larger declines in this probability, but there is no evidence that they experience a smaller boost in their exam scores from elite admission.

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 choose elite schools less often even when comparing to nearby high-SES students with the same entrance exam score. The paper's main findings offer one explanation for this result. Students from less advantaged backgrounds 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.

This paper fits, in part, into a vast literature on the effect of "school quality," or various characteristics thought to contribute to quality (e.g. teacher qualifications, other resources, or peer ability), on student outcomes.[2] We focus here on those studies that examine the academic benefits of admission to a competitive or "elite" public school. Because of the merit-based admissions systems used to allocate students, such studies typically use a sharp

[2] For a few examples, see 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 et al. (2010).

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) find that admission to competitive "exam schools" in Boston and New York has little effect on standardized achievement tests.[3]

Other studies use the regression discontinuity approach to estimate the benefit of attending a better school in the context of developing and middle income countries. Jackson (2010) finds a modest benefit of admission to high schools with higher-scoring peers in Trinidad and Tobago. Pop-Eleches and Urquiola (2011) find a similar benefit in Romania. In a much different study, Duflo et al. (2010) randomly assign 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.

This paper is also related to the literature on the effect of school quality on student dropout. 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. 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

[3] Dobbie and Freyer (2011) also find that the New York schools do not have an appreciable effect on long-run outcomes such as SAT score or college graduation.

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.

To our knowledge, this is the first paper to make use of Mexico City's matched high school entrance exam-12th grade exam data to estimate the impact of elite school admission on attrition and exam score performance. A parallel effort by Estrada and Gignoux (2011) uses a similar empirical strategy with one year of this 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.

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 school quality. Section 4 describes the data and Section 5 gives the empirical results from estimating quality. Section 6 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.[4] 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 curriculum.

After the scoring process, assignment of students to schools is carried out in July by 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

[4] 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.

students than the quota. If by the time a student's turn arrives, all of her 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.[5]

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. It is a benchmark of student and school achievement and progress.

3. Methodology

The principal goal of this paper is to determine how much (marginal) admission to an elite school changes students' probability of completing high school and their end-of-high school exam scores. Put another way, the econometric challenge is to estimate the effect on

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[5] 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.

It is not clear whether some students can improve placement outcomes by strategically (not) choosing an UNAM high school as first choice in order to take a particular version of the exam. Even if one exam is easier than the other, this is not a prevalent perception. If exam version is not a consideration, then listing all desired schools in the order of true preference is a dominant strategy. Choosing a school that fills up quickly as a first choice does not penalize students whose scores are too low for admission, because they are allowed to compete for seats in their second or lower options. Leaving aside the issues of ties and of students remaining unassigned if all of their choices fill up, the system can be thought of as lining up all students in order of score, then asking them to choose their favorite school from the list of remaining options when they reach the front of the line.

academic outcomes from admission to a school in an elite system versus the next-best option. The effect of interest is the change in Enlace taking or score due to elite school admission instead of admission to the student's next choice, provided that the next choice was not elite, holding Comipems score and all student characteristics, observed and unobserved, constant. This effect results from all aspects of a school that a student experiences as a result of being admitted, including the characteristics of the school itself (teachers, resources, etc.) as well as those of the student body that has been selected into each school.

The Comipems assignment mechanism permits a straightforward strategy for identifying the causal effect of elite school admission on outcomes, through a sharp regression discontinuity (RD) design. Each school j that is oversubscribed (i.e. it has 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 j is:

(1) $$Enlace_{ij} = g_j(Comipems_i) + \delta_j \, admit_{ij} + \epsilon_{ij}$$

where g_j is a function of Comipems score (in practice, a separate linear term on either side of the cutoff), $admit_{ij}$ is equal to 1 if student i was admitted to school j and zero otherwise, and $Enlace_{ij}$ is either a dummy variable for student i taking the Enlace or a continuous variable for Enlace exam score. The sample consists only of students who would have liked to attend school j when their turn for assignment arrived and have been barely admitted or rejected from the school. That is, they listed school j as a preference and when their turn for assignment arrived, all schools listed above school 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 who 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 in detail here. Consider a particular school, called school A, belonging to the elite school system, and suppose we define "close" to mean within 5 Comipems exam points of the cutoff. Determining the set of students above A's threshold is simple. Any student who was admitted to A but was fewer than 5 Comipems exam points above A's cutoff score is considered above A's threshold. This is the set of all students admitted to A who would be rejected if they lost 5 or fewer points. Since we restrict attention to those who would leave the elite system altogether upon rejection, students whose next-best school is elite and who have a high enough score to be admitted to that elite school are excluded. The corresponding set of students below A's threshold consists of students who were not admitted to any elite school, would be admitted to A if they gained at most 5 points, and who would not have been admitted to any other elite school upon gaining a number of points smaller than that necessary to attend A. This final condition ensures that the "below" group compares exactly to the "above" group, which would not be admitted to any other elite school if marginally rejected. Taken together, the "above" and "below" students form the RD sample for school A. The sample definition ensures that a student in the sample for A cannot belong to the sample constructed for any other elite school.

We see that $\mathbb{I}(Comipems_i \geq c_j)$ is an instrument that perfectly predicts $admit_{ij}$ for the selected sample. Provided that the control function g_j is specified correctly and is continuous at $Comipems_i = c_j$, $\hat{\delta}_j$ gives the estimated local average treatment effect (LATE) of admission to school j compared to admission to those schools attended by rejected students (Imbens and Lemieux 2008). There are many elite schools, so in order to give the average effect of elite school admission, equation (1) is estimated separately for each elite school and

$\hat{\hat{\delta}} = \sum_j \frac{N_j}{N} \hat{\delta}_j$ is computed, where N_j and N are the number of students at the threshold of school j and the total number of students in the sample, respectively. This is equivalent to taking the union of the disjoint school-specific samples, thus forming a sample of all students near the threshold of the elite system,and estimating one regression with threshold fixed effects and slope parameters that vary by threshold.

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 grade Enlace exams.[6] 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

[6] The 2010 data is used in order to match students from the 2006 Comipems cohort who took four years to complete high school.

survey turned in at the time of registration for the exam, but many students filled out only parts of the survey and non-response is high for some questions. Response rate is high for parental education and family income, exceeding 88% for each.

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 Mexicans. Matching is performed by name if no CURP match is found.

The "elite" high schools being considered in the regression analysis are the group of 16 high schools affiliated with the Instituto Politécnico Nacional (IPN).[7] 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 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 specific 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

[7] 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.

sample, the subsample consisting only of students located at the threshold of IPN admission,[8] and the IPN threshold subsample who took the Enlace, are in Table 1. Students on either side of the admissions threshold to an IPN school are substantially different from the full sample. 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. Unsurprisingly, students at an IPN threshold who actually make it to 12th grade and take the Enlace had higher middle school grade point averages and (slightly) better Comipems exam scores. Their Enlace scores are 0.36 standard deviations above the full sample average. [9]

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 "attrition" is indeed due to student dropout rather than some other feature of the data. The 2005 and 2006 Comipems assignment processes allocated 283,240 students from the sample to IPN and non-elite schools. But only 141,511 (50%) have a valid Enlace score reported. This number is consistent with the 55% graduation rate calculated by the Secretariat of Education for public high schools in Mexico City (Coordinación de Asesores 2011), when one considers that the (excluded) UNAM graduation rate exceeds the average rate and that a small number of assigned students will not begin high school at all. Table 2 shows correlates of assigned students taking the Enlace exam. Middle school GPA is a strong predictor of making it through high school and taking the Enlace. In Column 2, which includes both middle school fixed effects to account for different grading practices between schools and fixed effects for the school to which a student was assigned, a one standard deviation increase in GPA predicts a 16 percentage point increase in the

[8] 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.

[9] 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.

probability of graduating. Other factors, such as Comipems score, parental education, and family income are far less important and only minimally impact the chance of taking the Enlace.

5. Effects of IPN 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 taking the Enlace exam and, conditional on taking the Enlace, the exam score obtained. Thus the only sample used from this point forward is that of students at the threshold of an IPN school who fall out of the IPN system if rejected.[11] This corresponds to Column 2 of Table 1.

5.1 Probability of taking Enlace

Marginal admission to an IPN school has a large, significant negative impact on the probability of taking the Enlace exam. Figure 1 illustrates this graphically, centering students' scores about their school-specific cutoff score and plotting the Enlace taking rate in a 5 point window around the threshold. Table 3 confirms this finding, reporting the average effect of admission estimated using the regression discontinuity design. Column 1, which excludes any additional covariates, estimates that the probability of taking the Enlace decreases by 7.72 percentage points, compared to the mean probability of 53.65%. Adding covariates—middle school GPA, parental education, and family income—in column 2 does not change this result importantly.

Column 3 adds interactions between the covariates and admission in order to explore

[11] 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 a non-elite public high school.

whether the admission effect is heterogeneous with respect to middle school GPA and SES. The empirical specification is:

(2) $$take_{ijt} = \alpha_{jt} + \sum_j \big(\beta_{1j}(Comipems_{it}) + \beta_{2j}(Comipems_{it} * admit_{ijt}) + \delta_j \, admit_{ijt}\big) + \sum_k \Big(\gamma_k X_i^k + \mu_{1k}(Comipems_{it} * X_i^k) + \mu_{2k}\big(Comipems_{it} * X_i^k * admit_{ijt}\big) + \theta_k\big(X_i^k * admit_{ijt}\big)\Big) + \varepsilon_{ijt},$$

where 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 for each 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 θ_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 is strongly heterogeneous with respect to middle school GPA. All else equal, students with lower GPAs experience a larger decrease in probability of taking the Enlace. 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 -8.51 percentage points, and that $\hat{\theta}_{GPA}$ is 8.06. Then a student with a GPA one standard deviation below the mean experiences a $-8.51 - (0.74 * 8.06) = -14.47$ percentage point effect of admission on Enlace taking probability. Only students with very high GPAs, 1.43 standard deviations or more above the sample mean, are predicted to have a positive effect of admission on this probability. The admission effect differs by SES as well. Students with higher levels of parental education are not affected as negatively by IPN admission. Students with parental education one standard deviation below the mean experience a $-8.51 - (3.16 * 1.46) = -13.12$ percentage point effect on Enlace taking probability, while the effect is positive only for students with parental education 1.84 standard deviations or more above the mean. The results for family income are not statistically different from zero.

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 $\hat{\theta}_k * X_k$'s. Doing this, we find that 83% 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 positive impact on Enlace taking probability), with the rigor of the IPN schools more than offsetting this impact for all but the best-prepared and most-supported students.

5.2 Enlace exam performance

We now turn to the effect of IPN admission on Enlace exam score. Figure 2 suggests that there is a significant, positive effect. Table 4 reports the regression discontinuity results for this relationship. Column 1 does not include any additional covariates such as GPA or SES, and gives a highly statistically significant admission effect of 0.12 standard deviations on the exam. Adding covariates, the coefficient declines very slightly to 0.11. Column 3 adds interactions between admission and the covariates, but we fail to reject that there are no differential impacts (the p-value for an F-test of joint significance of the GPA, parental education, and income interactions is 0.69). Columns 4-6 suggest that this effect comes entirely from gains in math scores, between 0.21 and 0.22 standard deviations. The effect on Spanish scores, shown in columns 7-9, is indistinguishable from zero.

The results in section 5.1 make clear that there is non-random dropout in the sample of Enlace takers. Specifically, students admitted to an IPN school are on average 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. The results in Table 5 show that we fail to reject balance of the covariates at the time of assignment, as expected, but that after attrition GPA is unbalanced (about 1/7 S.D. higher for admitted students) as well as parental education (about 1/7 S.D. higher).[12] This differential attrition, due entirely to the effect of IPN admission, may bias estimates of the IPN admission effect on Enlace exam scores. To see why this is the case, suppose for example that the data generating process is as follows:

(3i) $$take_i = \begin{cases} 1 & if\ f(comipems_i) + \alpha_1 admit_i + \alpha_2 x_i + \alpha_3(admit_i * x_i) + \varepsilon_i > 0 \\ 0 & otherwise \end{cases}$$

(3ii) $$enlace_i = \begin{cases} g(comipems_i) + \delta admit_i + \beta x_i + v_i & if\ take_i = 1 \\ - & if\ take_i = 0 \end{cases}$$

where x_i is a student characteristic that affects both the chance of attrition and Enlace score. This is a simple selection model with a homogeneous treatment effect and differential attrition with respect to x_i. If attrition is conditionally uncorrelated with $admit$ so that it is balanced across the threshold, then the $\hat{\delta}$ obtained from estimating (3ii) by OLS for all Enlace takers is an unbiased estimate of the IPN effect on Enlace score for the group of students who took the Enlace. If $\alpha_3 \neq 0$, $\beta \neq 0$, and x_i is omitted from the Enlace regression:

(5ii*) $$enlace_i = f^*(comipems_i) + \delta^* admit_i + u_i$$

then δ^* may be biased. For example, if $\alpha_2 > 0$ and $\beta > 0$, then $E[u_i|admit_i = 1] > E[u_i|admit_i = 0]$. This leads to an upward bias on $\hat{\delta}$, by the standard omitted variables bias argument. The intuition behind this result is simple. If x_i is some measure of student ability and the IPN schools are more likely to fail out students with low ability, then failing to control for ability in the Enlace equation means that the "rejected" group is being compared to an "admitted" group that is missing more of its low-ability students. This makes the

[12] Section 5.3 gives a more detailed explanation of the estimation procedure used to obtain these results.

"admitted" group's average outcome appear higher than it is in comparison to the "rejected" group.

Even if $\beta = 0$, omitting x_i can lead to bias if the treatment effect is heterogeneous with respect to x_i. To show this, consider a modification of (3ii):

(3ii*)

$$enlace_i = \begin{cases} g(comipems_i) + \delta admit_i + \beta_1 x_i + \beta_2 (admit_i * x_i) + \nu_i & if\ take_i = 1 \\ - & if\ take_i = 0 \end{cases}$$

Suppose $\alpha_3 > 0$, $\beta_1 = 0$, and $\beta_2 > 0$. Omitting x_i and $admit_i * x_i$ when estimating this equation again leads to $E[u_i|admit_i = 1] > E[u_i|admit_i = 0]$ and biases $\hat{\delta}$ upward. Extending this framework slightly to allow a vector $\boldsymbol{X_i}$ of student characteristics instead of the scalar x_i, it is clear that omitting any column(s) of $\boldsymbol{X_i}$ and its interaction from (3ii*) may bias $\hat{\delta}$.

The magnitude of this bias is smaller when the missing characteristic has a small influence on differential attrition and/or Enlace score, or when it is highly correlated with $comipems_i$ or the included covariates. Fortunately, the controls that we have available (in addition to the Comipems score) are likely to be very good proxies for student ability. In particular, middle school GPA is both a useful predictor of differential attrition and of Enlace score. Yet adding this set of covariates to the Enlace score regression has practically no effect on the estimated admission effect, decreasing the coefficient from 0.12 to 0.11. It is on this basis, that the inclusion of intuitively and empirically relevant observables did not move the point estimate appreciably, that we argue that the admission effect is very likely to be positive, rather than purely an artifact of differential attrition.[13]

[13] We attempted to apply a modified form of Lee (2008) applied to the regression discontinuity case, in order to obtain sharp bounds on the treatment effect. But the differential is quite large and leads to wide bounds on the point estimate. Employing an instrumental variables strategy to address the attrition is infeasible, as it is unlikely that one can find a variable that affects differential attrition but not exam score.

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 notion that the excess attrition among IPN admittees is indeed due to drop-out 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, we show the results of two standard validity checks. The first is shown in Figure 4, which gives 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.[14] The second check is a test for a discontinuity in the observables at the admission threshold, at the time of assignment. This is done by estimating following equation for middle school GPA, parental education, and family income as dependent variables X_{ijt}:

(4) $$X_{ijt} = \alpha_{jt} + \sum_j \left(\beta_{1j}(Comipems_{it}) + \beta_{2j}(Comipems_{it} * admit_{ijt}) + \delta_j \; admit_{ijt}\right) + \varepsilon_{ijt}$$

Results are in Table 5. At the time of assignment (prior to attrition), the observables should be balanced across the threshold. Columns 1 through 3 show that we fail to detect any

[14] The test for a discontinuity in the density of the running variable, proposed by McCrary (2007), 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.

imbalance, both when testing each covariate separately or when estimating the equations jointly and performing a joint test for discontinuities.

All reported results are highly robust to changing the bandwidth. Results from regressions using 2 through 10 point window sizes, not reported fully 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 attrition result for the un-interacted model with covariates (Table 3, column 2) varies from -7.60 to -8.79. The corresponding Enlace score result (Table 4, column 2) varies from 0.11 to 0.14 standard deviations. The differential attrition 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 attrition 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 IPN schools reporting Enlace data in such a way that it is matched to the Comipems scores with a lower rate of success. 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 to 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 attrition, 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 should 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 more-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

Given the evidence that dropout risk in elite schools is higher for low-SES students and those with lower GPAs, we might expect that students with these characteristics request elite schools less often. 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 score c:

$$elite_{im} = \alpha_{mc} + \beta_c score_i + \theta_c educ_i + \epsilon_{imc}, \tag{5}$$

where $elite_{im}$ is a dummy variable equal to 1 if student i from municipality/delegation m chose an elite school as her first choice and $educ_i$ is years of parental education.[15] 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 θ_c's, which measure the marginal effect (though not a causal relationship) of parental education on elite school admission only for students with $score_i$ near c. Figure 3, Panel A graphs these coefficients and shows that for all values of Comipems score, higher education is correlated with higher rates of elite school preference. For example, at a score of 80 points, moving from elementary school graduate to bachelor's degree is associated with an increase in the probability of choosing an elite schoolof 15 percentage points (over a base rate of 60% for elementary graduates).[16] Panel B graphs the coefficient from (3) 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.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 are much less likely to list one as a first choice. The less favorable risk-reward tradeoff facing these students offers one way to rationalize this result.

[15] 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.
[16] 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.

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. At the same time, elite admission increases the probability of attrition from school for the vast majority of marginally admitted students, by 8.51 percentage points on average. The fact that this tradeoff is, in expectation, worse for those from less advantaged backgrounds offers one possible explanation for the lower rate at which qualified students of low SES apply to elite high schools.

The 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, 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.

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Table 1. Characteristics of students eligible for assignment

	(1)	(2)	(3)		
	All students	Students at an IPN threshold[a]	Students at an IPN threshold[a] who took Enlace	p-value for equality of (1) and (2)	p-value for equality of (2) and (3)
Male	0.46	0.60	0.56	0.00	0.00
Maximum of mother's and father's education	10.18	10.61	10.69	0.00	0.25
	(3.35)	(3.16)	(3.16)		
Family income (pesos/month)[a]	4,221	4,490	4,517	0.00	0.67
	(3,348)	(3,181)	(3,144)		
Middle school grade point average (of 10)	8.10	8.26	8.47	0.00	0.00
	(0.82)	(0.74)	(0.73)		
Number of schools ranked	9.31	10.49	10.48	0.00	0.97
	(3.59)	(3.74)	(3.71)		
Elite school as first choice	0.64	1.00	1.00	0.00	0.58
Allocated to any choice during initial assignment	0.84	1.00	1.00	0.00	1.00
Rank of allocated school from initial assignment, if applicable	3.30	4.39	4.38	0.00	0.90
	(2.90)	(3.11)	(3.04)		
Comipems examination score	63.74	73.55	73.84	0.00	0.02
	(17.95)	(6.33)	(6.51)		
Took Enlace examination (only for students assigned to a non-UNAM school)	0.50	0.54	1.00	0.00	
Enlace examination score (for those who took the exam)	-0.01	0.35	0.35	0.00	
	(0.99)	(0.77)	(0.77)		
Observations	354,581	8,244	4,423		

Note. Standard deviations in parentheses.

[a] Average 2005-2006 exchange rate was 10.9 pesos/dollar.

Table 2. Correlates of taking the Enlace exam

	(1)	(2)
Comipems score	0.14***	0.22***
	(0.01)	(0.01)
Middle school GPA	19.34***	19.32***
	(0.15)	(0.15)
Parental education (years)	0.35***	0.38***
	(0.03)	(0.03)
Family income (1000 pesos/mo)	0.13***	0.17***
	(0.04)	(0.03)
Middle school-year FE	Yes	Yes
Assigned high school FE	No	Yes
Observations	246,480	246,480
R^2	0.17	0.20
Mean of dependent variable	50.9	50.9

Note. Dependent variable is (took Enlace exam * 100).
Only students assigned to a non-UNAM school are included.
Robust standard errors, clustered at middle school-year level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Regression discontinuity estimates of effect of IPN admission on taking Enlace

	(1)	(2)	(3)
Admitted to IPN	-7.72***	-8.27***	-8.51***
	(2.19)	(2.23)	(2.23)
Middle school GPA		20.13***	16.50***
		(0.79)	(2.34)
Parental education (years)		0.63***	-0.18
		(0.19)	(0.60)
Family income (2005 pesos/mo)		0.20	0.77
		(0.19)	(0.60)
Middle school GPA * Admitted			8.06***
			(2.84)
Parental education * Admitted			1.46*
			(0.76)
Family income * Admitted			-0.48
			(0.76)
Threshold-year fixed effects	Yes	Yes	Yes
Observations	8,244	7,316	7,316
R^2	0.03	0.11	0.12
Mean of dependent variable	53.65	54.10	54.10

Note. Dependent variable is (took Enlace exam * 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 middle school GPA, parental education, and family income.

Middle school GPA, parental education, and income are de-meaned.

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

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

Table 4. Regression discontinuity estimates of effect of IPN admission on Enlace scores

	Enlace score (Math and Spanish)			Math score			Spanish score		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Admitted to IPN	0.12***	0.11***	0.12***	0.21***	0.21***	0.22***	0.00	-0.02	-0.02
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Middle school GPA		0.10***	0.10***		0.08***	0.08***		0.10***	0.10***
		(0.02)	(0.02)		(0.02)	(0.02)		(0.02)	(0.02)
Parental education (years)		-0.00	-0.01		-0.01	-0.01		0.00	-0.01
		(0.00)	(0.01)		(0.00)	(0.01)		(0.00)	(0.01)
Family income (1000 pesos/mo)		-0.01*	-0.00		-0.00	-0.00		-0.01**	-0.01
		(0.00)	(0.01)		(0.00)	(0.01)		(0.00)	(0.02)
Middle school GPA * Admitted			-0.08			-0.07			-0.07
			(0.07)			(0.07)			(0.07)
Parental education * Admitted			0.00			-0.01			0.01
			(0.02)			(0.02)			(0.02)
Family income * Admitted			0.01			0.03			-0.02
			(0.03)			(0.03)			(0.03)
Threshold fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,423	3,958	3,958	4,423	3,958	3,958	4,423	3,958	3,958
R^2	0.21	0.22	0.22	0.18	0.18	0.19	0.13	0.14	0.14
Mean of dependent variable	0.35	0.35	0.35	0.41	0.41	0.41	0.21	0.21	0.21

Note. Dependent variable is (took Enlace exam * 100).
All regressions include threshold-specific coefficients for Comipems score and (Comipems score * admitted). Columns (3), (6), and (9) include coefficients for (Comipems score * covariate) and (Comipems score * covariate * admitted) for middle school GPA, parental education, and family income.
[a] Average 2005 exchange rate was 10.9 pesos/dollar.

Robust standard errors, clustered at middle school level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Balance of covariates before and after assignment

	Before attrition			After attrition		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Middle school GPA	Parental education	Family income (1000 pesos/mo)	Middle school GPA	Parental education	Family income (1000 pesos/mo)
Admitted to IPN	-0.01	0.17	-0.10	0.10***	0.43**	-0.01
	(0.03)	(0.14)	(0.14)	(0.04)	(0.20)	(0.19)
Threshold fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,232	7,458	7,364	4,419	4,024	3,979
R^2	0.06	0.02	0.02	0.07	0.04	0.03
Mean of dependent variable	8.26	10.61	4.49	8.47	10.69	4.52
S.D. of dependent variable	0.74	3.16	3.18	0.73	3.16	3.14
p-value, joint significance of admission coefficients[a]			0.33			0.01

Note. Dependent variable is (took Enlace exam * 100).

All regressions include threshold-specific coefficients for Comipems score and (Comipems score * admitted).

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, 2, and 3 or 4, 5, and 6. In each case, the equations are jointly estimated with seemingly unrelated regression.

Figure 1. Enlace taking rate for students near IPN system cutoff.

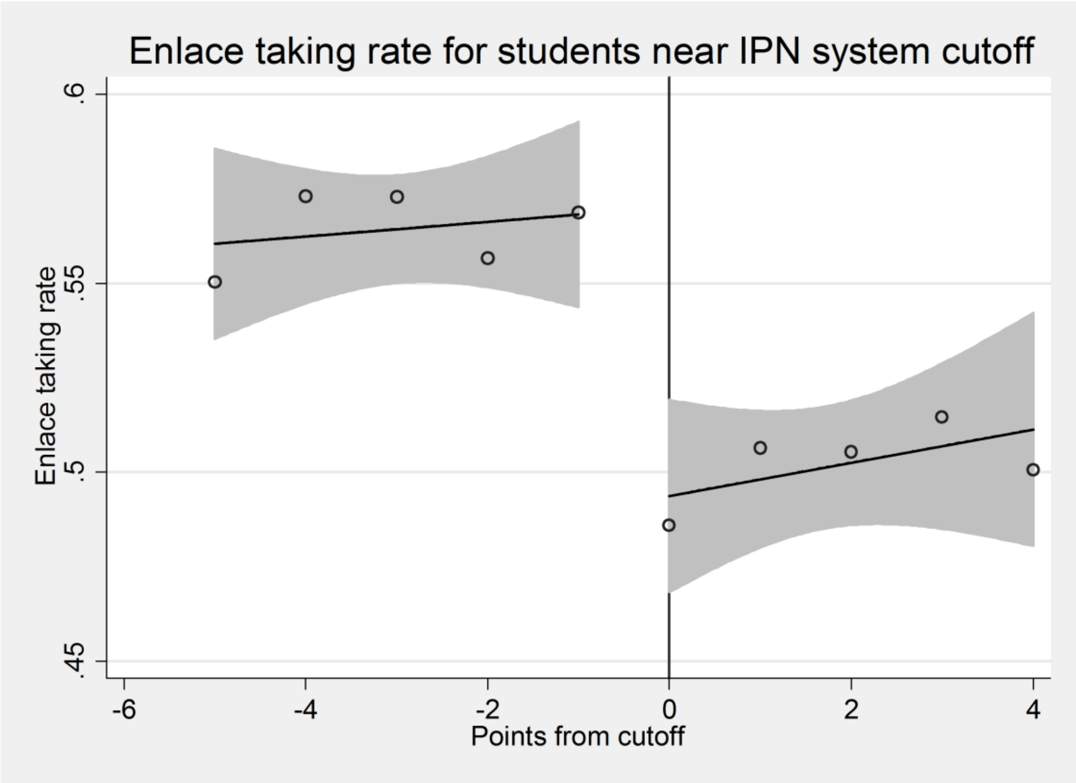


Figure 2. Enlace performance for students near IPN system cutoff.

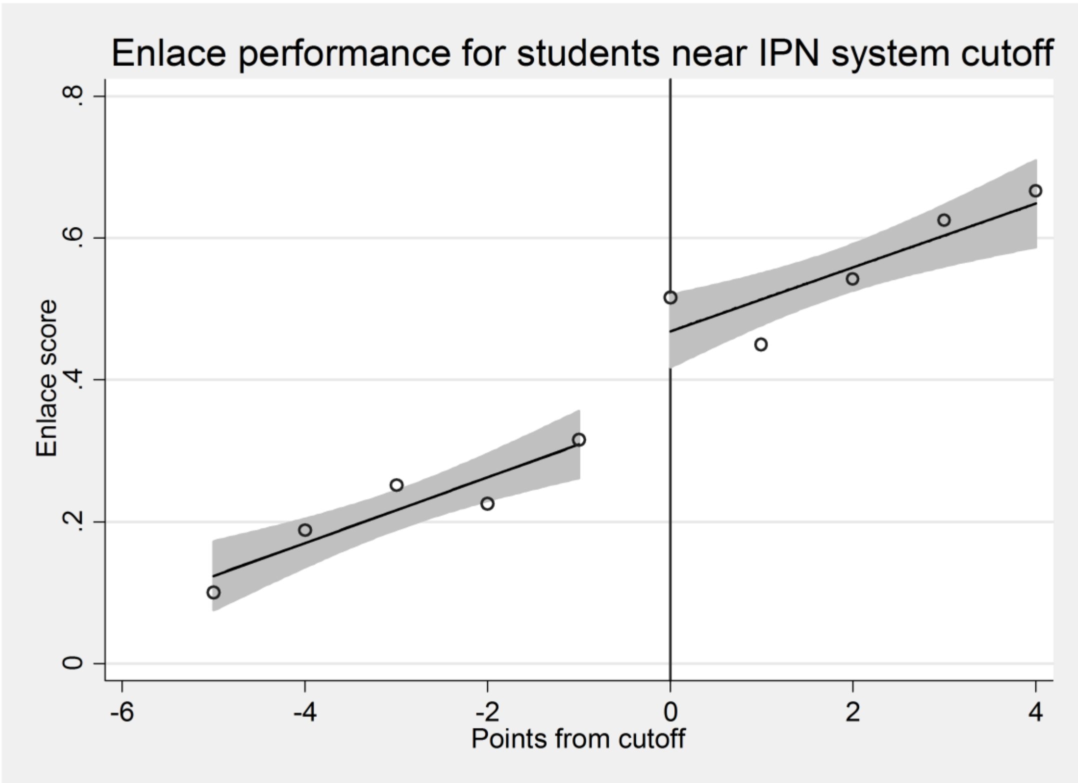
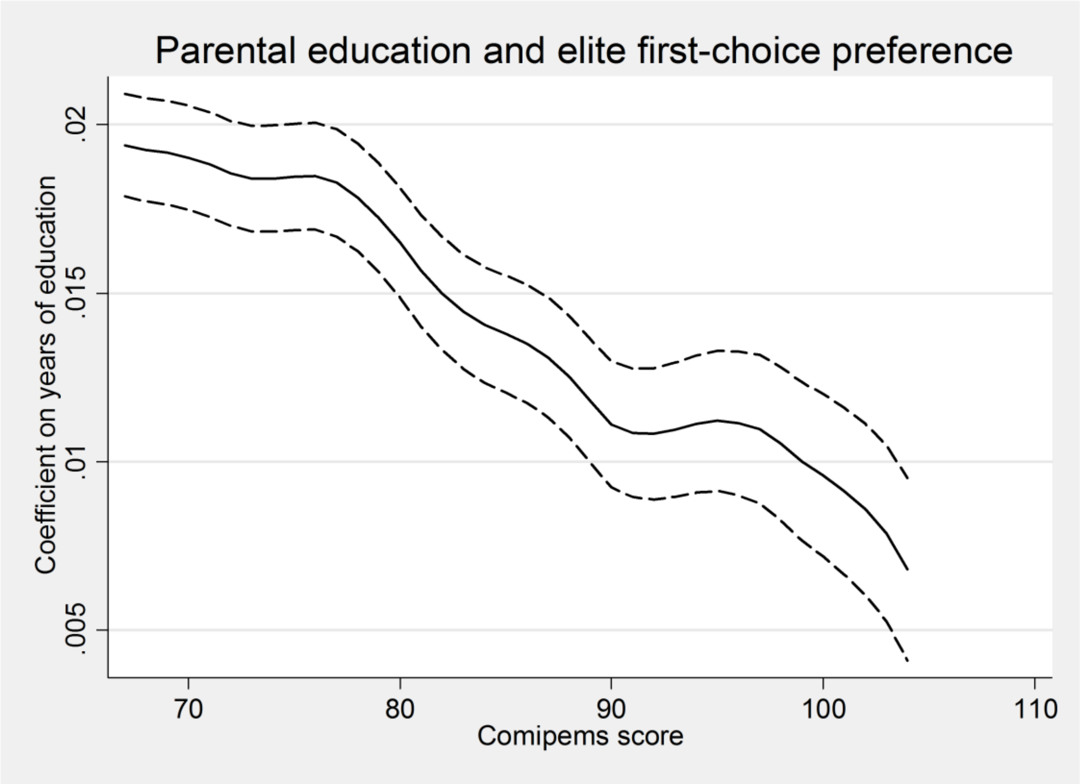
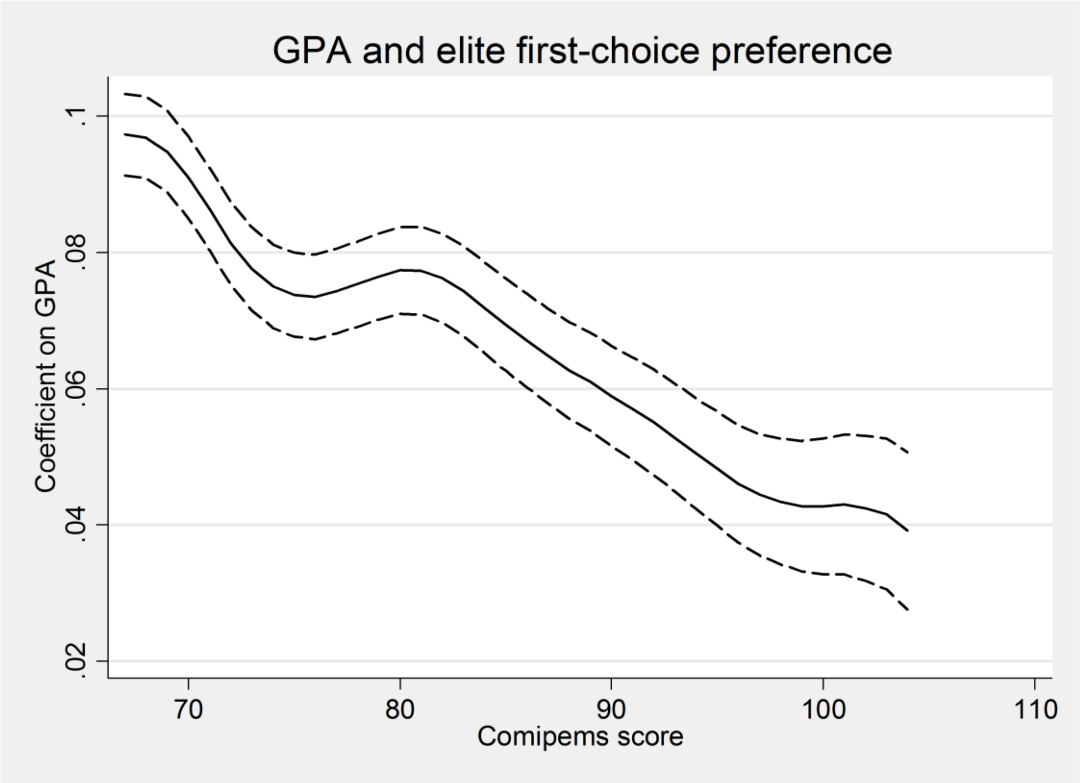


Figure 3. Partial correlation of student characteristics with elite school first-choice preference
Panel A. Years of education



Panel B. Grade point average



Note. Solid line is a smoothed line through the $\hat{\theta}_c$ coefficients from estimating equation (5). Dotted lines are the 95% confidence intervals for the estimated $\hat{\theta}_c$'s.

Figure 4. Density of student scores around IPN system cutoffs.