A Better School but a Worse Position? The Effects of Marginal School Admissions in Mexico City*

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Abstract

This paper provides causal evidence on the effects of marginal admissions to better middle schools on students' academic performance, self-perceptions, aspirations, and subsequent schooling choices. Students in Mexico City are assigned to public middle schools based on the results of a placement exam. The morning shift in double-shift schools is often oversubscribed, leading to the stratification of school shifts by test score results. Using the admission cut-offs as exogenous variation in school offers, I find that students who attend more selective schools experience small improvements in standardized language scores but perform worse on non-standardized assessments.These students have lower grade point averages and are less likely to pass all the courses required to complete middle school. I provide evidence to suggest that students evaluate themselves based on their relative performance: marginally admitted students to the more selective shift report feeling academically inferior to their peers, have lower self-reported perseverance and time management scores, and are more likely to shift their aspirations and subsequent schooling choices from academic to vocational programs. These findings highlight the importance of frames of reference in educational settings and the potential trade-offs between a better school and a worse position in the ability distribution.

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1 Introduction

It is commonly believed that attending schools with more resources and higher-achieving peers can improve students' human capital, labor market opportunities and social mobility. After all, children who attend better schools might be exposed to more experienced or talented teachers or peers who could help them study, be less disruptive (Lazear, 2001), act as role models or become a positive influence (Kremer and Levy, 2008). However, better schools can also be more challenging environments. Students might face higher academic standards and find themselves in a lower position in the school ability distribution. If the level of instruction is not appropriate for students' knowledge or ability (Duflo et al., 2011), if the educational system only benefits 'star' students (Attewell, 2001) or if having a lower ordinal class rank negatively affects individuals' perceptions of their ability, identity (Marsh and Parker, 1984; Akerlof and Kranton, 2000), confidence (Murphy and Weinhardt, 2014) or behavior (Cicala et al., 2017), the benefits of attending a better school may not materialize.

This paper measures these trade-offs in the context of middle school admissions in Mexico City and offers new causal evidence on the effects of attending more selective schools on the academic performance, self-perceptions, aspirations and subsequent academic choices of students at the margin of admission to a more selective school. To overcome selection bias, I rely on a regression discontinuity design that compares barely-admitted and barely-rejected students across hundreds of oversubscribed schools in double-shift school buildings. In this setting, shift assignment within a building depends on the results of a placement exam, which leads to the stratification of shifts by academic ability. Students who receive an offer to the morning shift find themselves in school environments with higher-ability peers, more educated principals, and more incentivized teachers, albeit with slightly lower teacher-student ratios. However, they are also more likely to find themselves at the bottom of their school academic ability distribution, whereas those marginally rejected are more likely to be at the top.

An empirical literature has largely hypothesized that attending better schools should boost student achievement and has focused on estimating the effects on learning outcomes, as measured by standardized tests.[1] This literature has found that for students at the margin of admission,

[1] In this literature, a better school is usually defined as a school with higher-achieving peers and in some cases

attending a better school (or classroom) has either no effect (Clark, 2010; Lucas and Mbiti, 2014; Ajayi, 2014; Abdulkadiroğlu et al., 2014; Dobbie and Fryer Jr, 2014; Duflo et al., 2011) or modest positive impacts on test scores (Pop-Eleches and Urquiola, 2013; Kirabo Jackson, 2010; Hoekstra et al., 2016; Park et al., 2015).[2] However, we have less credible evidence on how other margins might be affected.[3] This evidence is important as various studies have found that long-run outcomes may be influenced by features not captured by standardized tests (e.g. Ludwig and Miller, 2007; Chetty et al., 2011; Jackson, 2016) and have emphasized the need to consider behavioral responses to interpret reduced form estimates (Pop-Eleches and Urquiola, 2013; Albornoz et al., 2011).

I show that learning gains in standardized tests can coexist with worse school-level performance relative to attending the counterfactual school. On the one hand, an offer to the more selective morning shift improves students' performance on language scores by 0.04-0.06 standard deviations (s.d.), as measured by standardized tests completed in 7th grade and a high school entrance exam taken in 9th grade. I find no statistically significant average impacts on math scores, but students who had a weaker performance in primary school and those with parents with lower levels of education experience gains of 0.04-0.08 s.d. in the math portion of the high school entrance exam. This suggests that, at least in measures of learning, disadvantaged students are not less likely to benefit from attending better schools.

On the other hand, applicants who score just above the admission threshold and who are offered a position in the more selective morning shift school have worse average performance on school-based assessments. Their grade point average (GPA) in 8th grade is 0.2 points lower (out of 10 points) than that of students of similar ability who had an offer for the less selective school (the afternoon shift in the same facility). They are also, on average, 4 percentage points more likely to fail a class (a 17% increase), and 3 percentage points more likely to experience a delay in grade progression.[4]

as a school that has more resources.

[2]For the average student, Duflo et al. (2011) find positive effects from having higher ability peers. Park et al. (2015) find relatively larger effects of 0.39 s.d. for college entrance examinations in magnet schools in China.

[3]Two recent exceptions outside the U.S. are Pop-Eleches and Urquiola (2013), who report the behavioral effects of attending better high schools in Romania and Dasgupta et al. (2017), who report effects on measures of socio-emotional and non-cognitive traits for college students in India.

[4]In this context, school delays are a widespread issue: a survey conducted with a random sample of Mexico City youth under the age of 17 showed that 42% of males and 27% of females had experienced at least one spell

The negative effect on school-level assessments translates into real costs for students: those who were barely above the morning school admission threshold are one percentage point less likely to receive a middle school certificate within two years of the predicted graduation date (corresponding to a 25% increase relative to the counterfactual group). These effects are in line with recent empirical evidence showing that attending an elite or better institution can increase the risk of dropping out (Ortega Hesles, 2015; Dustan et al., 2016).[5]

To shed light on the socio-emotional effects of placing into more selective schools, I look at differences in measures of perseverance, time management, and aspirations. Recent theoretical and empirical work highlights the possibility that a lower ordinal rank may negatively affect behavior, non-cognitive skills or attitudes (Pop-Eleches and Urquiola, 2013; Elsner and Isphording, 2017a,b; Dasgupta et al., 2017; Murphy and Weinhardt, 2014; Cicala et al., 2017).[6] Supporting the hypothesis that students internalize their position within a school (either relative to other students or to an absolute higher standard), students who barely place into a better school are more likely to report that they feel academically weaker relatively to their peers, particularly in math. They also obtain lower scores in self-reported measures of perseverance and an index of their ability to prioritize and complete tasks.

While changes in socio-emotional measures may reflect respondents' implicit comparisons to their peers rather than authentic effects on their skills, self-perceptions are important if they affect how students form aspirations and make decisions. I find evidence consistent with this channel: an offer from a better school leads to a two percentage point decrease in their aspiration to attend college, instead aspiring to pursue a technical (non-college) degree. Importantly, students' subsequent educational choices are also affected. In Mexico, students can choose among

in which they had failed a grade or were delayed (González, 2016).

[5] Dustan et al. (2016) use a regression discontinuity for admission to the prestigious IPN high school in Mexico City and find that admission to the IPN elite high school increases the probability of dropping out (not taking the universal standardized test) by 7.7 points. By bounding their estimates to account for this attrition, they find increase in end-of-high school scores of 0.12 s.d..Ortega Hesles (2015) finds that those with more competitive high school offers have a 3 percentage point lower probability of graduating on time.

[6] Pop-Eleches and Urquiola (2013) find evidence that marginal students who get offers to better schools might be more likely to be bullied and feel worse relative to peers. In the context of college students, Dasgupta et al. (2017) show that attending a higher-quality college lowers females' risk aversion and overconfidence and males' extraversion and conscientiousness. Cicala et al. (2017) present results from lab experiments showing that students might be more likely to misbehave when they know they perform relatively worse on a task. Elsner and Isphording (2017b) associate lower academic rank with a higher likelihood of smoking, drinking, having unprotected sex and engaging in fights. Murphy and Weinhardt (2014) associate worse ordinal rank with lower confidence.

vocational and academic tracks in high school. Using data from students' high school application portfolios, I find that the offer to attend a better middle school increases the share of vocational high schools that students apply for by the end of middle school by one percentage point (a 4% increase).

Worse school performance might be reflective of higher school standards, teachers' implicit comparisons when assigning grades and/or changes in students' behavior. While I find changes in students' socio-emotional skills, I do not find increases in student truancy or other changes in student behavior. I also rule out the possibility that achievement might be negatively affected by time of day, since the results are similar when comparing students in oversubscribed (higher-achieving) afternoon shifts vs. (lower-achieving) morning school options. Neither do I find compelling evidence to suggest that these effects are driven by a lower teacher-student ratio.[7]

The paper is structured as follows. Section 2 describes the institutional context and the middle school assignment mechanism. Section 3 describes the data sources and how the sample is selected. Section 4 discusses the empirical strategy and section 5 its validity. Section 6 presents the main results. Section 7 discusses alternative interpretations of mechanisms. Section 8 concludes.

2 Institutional Context

2.1 The Schooling System in Mexico City

Mexico's education system is organized into preschool, basic education, high school and higher education. Basic education is compulsory and consists of six years of primary school (1st to 6th grade) and three years of middle school (7th to 9th grade). High school consists of three years (10th to 12th grade). This project focuses on students' experiences in middle schools in Mexico City. About 85% of all students in the city attend public middle schools.[8] All middle schools

[7] This would also be harder to reconcile with the gains in standardized tests.

[8] There are three main types of middle schools: technical (33% of students), academic or general (65%) and television-based schools (2%). The distinction between technical and general schools emerged at a time when middle school served as a transition into the labor market and technical middle schools were vocational in focus. Today, the key difference is that technical middle schools complement the core curriculum with additional vocational courses (e.g., accounting, secretarial skills, automobile mechanics, computers, etc). In contrast, very few students in Mexico City attend television-based schools, which were originally designed to serve remote rural areas. For a description of the television-based schools, see Fabregas (2017).

operate under the same core curriculum and students must pass every core curriculum subject (obtaining a minimum grade of 6 points out of 10) in order to earn a certificate of completion. If a student fails a subject, they have the option of taking a make-up exam that evaluates the contents of the entire period.[9]

The coverage rate for middle school is 88% at the national level, but enrollment statistics collected at the school level suggest that in Mexico City, enrollment and completion of middle school is nearly universal (INEE, 2016). However, a recent survey conducted with a random sample of adults under the age of 29 showed that 6% of students (8% of men and 4% of women) started but never completed middle school (Blanco et al., 2014).[10] Enrollment in high school is also high at approximately 93% (INEE, 2015).

Like several other countries that seek to reduce the unit costs of education but guarantee access, a large fraction of primary and middle schools in Mexico City operate on the basis of double-shifts in the same building, each shift operating like an independent school.[11] In over 60% of middle schools in the city, students attend either a morning (approximately from 7:30 to 13:40) or an afternoon shift (approximately 14:00 to 20:10). Henceforth I refer to each shift as a 'school' and each school building as a 'facility'.

2.2 Middle School Enrollment

The allocation of students to public middle schools is done through a centralized assignment process run by the local office of the Public Education Secretariat, or *Secretaría de Educación Pública* (SEP). Each February, families with children in 6th grade are requested to submit an application form that asks them to rank their three preferred middle school facilities in order of preference and their overall preferred shift (morning or afternoon).[12]

Families can list any three facilities city-wide regardless of where they live. Each incoming cohort has approximately 140,000 students, and they have the chance to select schools out of

[9] If a student fails five courses or more, they are required to repeat the entire year.

[10] One potential reason for this discrepancy could be the movement of students across states, especially from the neighboring State of Mexico.

[11] Double-shifting schooling is common in several other countries, including Brazil, India, Costa Rica, Malaysia, Senegal, Zimbabwe, South Africa, Namibia and Tanzania (Bray, 2000; Denham, 2009).

[12] For the years I study, the questionnaire only asked about the overall preferred shift, not their shift preference for each facility.

a potential list of 500 facilities (corresponding to approximately 800 different schools). The SEP's website lists all schools in Mexico City by location but does not provide any additional information about their quality.[13]

In contrast to primary school, in which enrollment priority is given by students' distance to the school and enrolled siblings, enrollment priority for middle school is given on the basis of a placement exam.[14] The placement exam takes place in May or June, four or five months *after* families have submitted their facility preferences.[15] The 60-point exam is an aptitude test intended to measure students' basic competencies in reading comprehension, sentence completion, arithmetic, geometry and completion of series. Families can officially request a school change once the final placement lists have been published or try to directly enroll their children in a different under-subscribed school. I discuss the extent to which students comply with their school assignment in Section 6.

The Assignment Algorithm. Assignment to middle school relies on an immediate acceptance mechanism.[16] Each year, a school has a predetermined number of seats. For applicants who prefer the morning shift (about 95% of students), the algorithm will attempt to place the student in the morning shift of their first choice facility in order of their placement exam score and up to school capacity. Once the morning shift of a given facility is full, the algorithm will assign as many students as possible to the afternoon shift of that same facility.[17] Once a student is placed, they are removed from the applicant pool. If a student cannot be placed in their first choice facility, the process continues in a similar fashion for their second and third facility choices, always attempting to assign students to the morning shift first and then to the afternoon shift.

[13] Recently, some websites managed by NGOs have started to provide school ranking information based on the raw standardized test score performance of students. For instance: www.mejoratuescuela.org.

[14] This exam is known as the *Instrumento de Diagnostico para Alumnos de Nuevo Ingreso a Secundaria* or IDANIS.

[15] By law all children are entitled to a place in middle school; therefore taking the placement exam is not mandatory. Students who do not take the exam are simply awarded a grade of zero and allocated to a school through the same assignment mechanism. For the cohorts I observe, 2% of applicants are assigned to a school but do not take the placement exam.

[16] The mechanism, which is similar to the one previously used in Boston, is neither strategy-proof (since parents might misrepresent true school preferences in order to ensure placement in a preferred facility) nor fair (in the sense that highly-ranked students can end in less preferred schools while a lower-ranked student might be admitted to a more preferred school). For a detailed discussion of these issues, see Abdulkadiroglu and Sönmez (2003).

[17] Those students who prefer an afternoon shift are only considered for the afternoon shift of a given facility, but they do not get preferential treatment in those allocations. Instead, these students compete for slots with students who had morning shift preferences, but did not obtain a place in the morning shift.

If their first, second and third facility choices are already full, students are then assigned to facilities that are located close to one of the facilities they selected. For a given placement score, ties are broken by having siblings in the school, proximity to the school and student's date of birth.

School capacity constraints generate two types of cut-offs across schools: cut-offs within the same facility (for those facilities that have two shifts) and cut-offs across different facilities (mostly from oversubscribed afternoon shifts to the next facility or across-facilities if the facility had a single shift). For reasons discussed in section 6, my main empirical analysis focuses on the comparison within facilities, though later I show that many results hold when using across-facility cut-offs. In 2011, approximately 80% of all applicants placed in their first-listed facility and of those, 60% in their first-listed school. About 8% of students placed in the facility they listed second, 4% in the facility they listed third and the remaining in a school they did not list at all.

Since the mechanism is not strategy-proof, listing a facility does not necessarily imply that families would truly prefer that facility over other options.[18] However, there is no strategic advantage in choosing a less-preferred shift within a facility. In addition, for purposes of the empirical strategy I employ, there is no reason to believe that strategic behavior or mistakes in school selection would differ around cut-offs, since families select schools before students take the placement exam and cut-off scores are revealed. I show empirical evidence to support this assumption in section 5.

2.3 High School Enrollment

Admission to public high school also relies on a competitive process in which students compete to access one of nine different high school subsystems.[19] The admission process also depends on students' high school preferences and the results of a high school placement exam. Each March,

[18] In addition, the typical reason to behave strategically -i.e. it is risky to list a highly competitive facility- might be compounded by the fact that there is an additional risk in listing a an option that is geographically close to a much less preferred facility.

[19] This process is managed by a centralized commission, the *Comisión Metropolitana de Instituciones Públicas de Educación Media Superior* or COMIPEMS. There are some public high schools that are not part of this process, but it is estimated that less than 10% of all students overall matriculate in public high schools outside this system (Avitabile et al., 2017).

9th grade students who wish to enroll in a public high school submit a form that asks them to rank up to 20 high school choices. In order to register for the exam, students are asked to complete a background questionnaire, which includes questions about their experiences in middle school, their academic aspirations, self-perceptions and their preparation for the high school entrance exam.[20] In recent years, questions have rotated, with different graduating cohorts completing slightly different versions of the background questionnaire.

Students can rank any combination of academic or vocational high school tracks. All tracks grant students a high school certificate that allows them to continue to higher education. However, those who attend vocational tracks are significantly less likely to enroll in a tertiary education institution and more likely to work after graduation (Avitabile et al., 2017). Overall, students can choose from over 260 high school facilities. However, the high schools with by far the most demand are the 'elite' schools associated to National Universities.[21] Admission to the elite subsystems also has a minimum middle school GPA requirement of 7 (out of 10) points. In June of 9th grade, three to four months after submitting their high school preferences, applicants take a standardized exam consisting of 128 multiple-choice questions, covering school curriculum material and general aptitude skills for language and math.

Assignment to high school is done through a serial dictatorship assignment mechanism with priority given on the basis of the high school exam result (Dustan et al., 2016).[22] Because all applicants are guaranteed a slot for high school, there are two ways students might not be assigned a seat. First, they might not be assigned a seat if they do not list a school for which they meet the minimum entrance exam score. In this case, they are allowed to enroll in any other high school with open spaces. Second, they will not be assigned to a high school if they do not obtain a middle school certificate by the time the assignment takes place.

[20] This questionnaire is completed online and then physically submitted at the time of registration. Applicants can skip questions, but the system requires them to complete the questionnaire to complete their registration. Before completing the background questionnaire, students read a screen indicating that answers will only be used for research purposes and that they will have no impact on their likelihood of admission.

[21] These include the 16 high schools associated with the *Instituto Politecnico Nacional* (IPN), a national university focusing on science and engineering, and the 14 high schools associated with Mexico's National University, the *Universidad Nacional Autonoma de Mexico* (UNAM). One key feature of admission into a high school associated to UNAM and that makes it very attractive is that UNAM high school students with a pre-determined GPA are also guaranteed admission to the highly competitive university.

[22] The algorithm for assignment in high school ranks students by their high school entrance exam score. It then goes down the student ranking, assigning students to their preferred choice with open seats.

3 Data and Sample Selection

3.1 Data

This study combines four primary sources of data (see Figure 1 for timeline). All individual level databases were merged and de-identified at the SEP offices in Mexico City. A detailed description of all data sources and matching procedures can be found in appendix B. Table A1 in the appendix reports the matching rates for different data sources.

1. Middle School Assignment Data: Student-level administrative records held by Mexico City's SEP office that comprise the universe of 6th grade students who applied for a seat in a public middle school in February of 2011 or 2012 (henceforth the 2011 and 2012 cohorts).[23] The two combined cohorts of applicants include observations for over 289,000 students. The data contain information on students' three top middle school choices and their placement exam score, as well as background characteristics such as gender, date of birth, primary school attended and parental education. This database is complemented with administrative records on the number of available seats for each middle school, which allows me to replicate the assignment algorithm.

2. Low-Stakes Standardized Test Data: Standardized tests administered to all students in basic education in public and private schools towards the end of the school year. The results from this exam did not affect students' records and were mainly used to diagnose overall student performance in the country.[24] The exam tested knowledge of mathematics and Spanish. Because the exam was discontinued in 2014, I use individual-level results from 2010 to 2013. Therefore I can observe results for 5th and 6th grade (pre-assignment) and results for 7th grade for both cohorts (one year after middle school assignment) and 8th grade for the 2011 admission cohort (two years after assignment). The reported scores are standardized to have a mean of zero and a standard deviation of one for each cohort of middle school applicants.

3. High School Entrance Exam, Background Questionnaire and Certificates: The high school admissions database compiles information on students' high school placement exam scores,

[23] The SEP does not keep assignment records for students previous to 2011. The 2011 and 2012 cohorts were chosen because they could be linked to their high school applications within two years of their expected middle school graduation date. I expect to obtain data for the 2017 high school applicant cohorts in the future.

[24] These exams are known as the *Evaluación Nacional de Logros Académicos en Centros Escolares* or ENLACE.

high school choices and their responses to the background questionnaire.[25] The background questionnaire includes questions about students' socio-demographic characteristics, aspirations, self-reported grades, measures of perseverance, and their perceived ability to complete different tasks. This database is also linked to administrative records indicating whether students had earned a middle school certificate by the time the high school assignment took place.

4. School Personnel Data: School-level data reported by each school at the beginning of each academic year on the number of students enrolled and the average characteristics of the teaching personnel.

I highlight some data limitations. First, I observe outcomes only for students who register to take the high school placement exam in Mexico City.[26] Because I limit the sample to students who attended middle school in Mexico City, out-of-state registration is less of a concern. Similarly, I do not observe students who never take the high school exam because they prefer to enroll directly in a private high school.[27] Reassuringly, as will be shown later, patterns of attrition by treatment assignment are similar across data sets and pre-treatment characteristics are balanced on the matched sample. Third, because some questions in the background questionnaire rotate over time, certain outcome measures are only available for the 2011 or 2012 cohort, but not both.

3.2 Sample Selection and Summary Statistics

The analytic sample consists of middle school applicants who completed 6th grade in a public primary school in Mexico City in 2011 or 2012.[28] In order to implement a regression discontinuity design, the sample is restricted to applicants who listed an oversubscribed morning school in a

[25] There are two versions of the exam, one for those who list a high school affiliated with the national university as their first choice and another one for everyone else. Both versions are constructed to be comparable in terms of difficulty. I do not find differences around the cut-offs in students' likelihood of taking different versions of the exam.

[26] Students can also choose to register for the high school exam in the neighboring State of Mexico; however, the SEP offices in Mexico City did not have access to this information.

[27] Some authors have calculated that about 14% of students attend private high schools (Blanco et al., 2014). However, this includes students who were always in the private system. Using data from the *Encuesta Nacional de Desercion en la Educacion Media Superior*, I calculate that less than 8% of students who attend a public middle school enroll in a private high school. However, it is common for students to only opt for private options after taking the high school entrance exam, but failing to obtain a seat in one of their preferred options.

[28] Approximately 9% of students who applied for a middle school seat live in the neighboring State of Mexico and another 1% in another state. Because the outcome data is limited to outcomes for students in Mexico City, by focusing on students living and attending public basic education in Mexico City, I reduce the likelihood of differential attrition driven by students who decide to attend a closer school in one of these states if they do not place in their preferred middle school.

double-shift facility as their first option.[29] The sample is further restricted to applicants who preferred morning-shifts (95% of the sample) and who were not marked as 'special cases' by the SEP (1%), as the assignment algorithm worked differently in those cases. Since ties are broken by giving priority to certain students, I restrict the sample to students who do not score right at the cut-off of admission for a given school.[30] Finally, the analysis is restricted to individuals who can be matched across data sets within two years of their predicted graduation date.

From an initial sample of 285,739 applicants, I end up with a complete analytic sample consisting of 82,566 students who listed one of 292 oversubscribed facilities (139 in 2011 and 153 in 2012) as their first choice (from which 32,181 students are within a narrow bandwidth of 5 points from their first-choice school cut-off).

Table 1 shows the mean and standard deviations for: (i) the full sample of students who applied for a seat in a public middle school, (ii) the sample restricted by the conditions discussed above (analytic sample), and (iii) those in the analytic sample who fall within 5 points of either side of the admission cut-off (RDD sample). Overall, the sample of students analyzed has similar demographic characteristics to the full population of applicants. About 50% are women; their average age is 12.3 years and less than half have parents who report having studied beyond middle school. The results in the placement exam are slightly higher in the analytic sample relative to the entire population of applicants (35 vs. 32 points, respectively). This difference in achievement is also reflected in the results from standardized tests in 5th and 6th grade, which are about 0.20 s.d. higher for the analytic sample. Relative to other papers that have focused on elite school admissions, the sample of students I analyze is not extremely 'selective'. This is unsurprising because the majority of students place in their first choice facility and there is a fairly wide distribution of placement score cut-offs in the analytic sample (Figure A1 in the appendix).

[29] I define oversubscribed schools as having at least 10 students who did not place in their first choice school because of capacity constraints and who are within 5 test score points of the cut-off. Changing this definition from having at least one student not placing or having at least 20 not placing does not alter the results.

[30] Because students are selected based on distance to school, date of birth and having siblings in the school, this would violate the assumption that selection is 'as-random' around the cut-off. Additionally, Fort et al. (2016) advise dropping observations at zero distance from the threshold in stacked designs to avoid bias. Importantly, all results are robust to including students who score right at the cut-off.

4 Empirical Strategy and Sample

4.1 Empirical Strategy

Capacity constraints give rise to admission score cut-offs within each facility with oversubscribed morning shifts. To estimate the causal effects of marginal admission to a more selective school, I employ a regression discontinuity design (RDD) that compares the outcomes of students who were barely admitted into their first school choice (the morning shift of a given facility) against those who were barely admitted into the next available school (the afternoon shift in that same facility). This strategy overcomes the identification challenge that arises from confounding impacts from attending a preferred school with student self-selection.

The forcing variable (the placement score distance to the school cut-off) is re-centered to the specific school cut-off. Following Abdulkadiroğlu et al. (2014) and Pop-Eleches and Urquiola (2013), I stack the cut-offs, with the resulting estimates providing average treatment effects for all cut-offs, weighted by the number of students marginally admitted and rejected.[31] I estimate the following local linear specification, limiting the analysis to a narrow window around the admission threshold:

$$y_{isc} = \alpha + \beta Above_{isc} + \lambda f(ScoreMargin_{isc}) + \delta f(Above_{sc} \times ScoreMargin_{isc}) + \theta_{sc} + \epsilon_{isc} \quad (1)$$

y_{isc} is an outcome variable for individual i, applying to facility s in cohort c. $Above_{isc}$ indicates whether the placement score was above the (morning) cut-off, $ScoreMargin_{isc}$ is the distance (in points) to the cut-off score for the morning shift of a student's first-choice school, and θ_{sc} refers to facility - year fixed effects. Including pre-treatment characteristics is not necessary for identification, but to improve precision I also control for gender, age, whether they had a sibling in the school, if they live nearby the school, pre-treatment standardized test scores, disability status and an indicator variable for whether their mother had completed middle school.

Since students do not perfectly comply with school assignment, β estimates intent-to-treat effects, measuring the causal effect of having an offer to the morning shift for a given facility.

I use Akaike's information criterion to determine the order of the polynomial to be used and I opt for a linear specification. Given the discrete nature of the placement exam scores, the

[31] In this setting, each student is only used once in the analysis.

relatively narrow range of scores and the fact that I present results for multiple outcomes, I opt to consistently show results for a bandwidth of 5 points around each cut-off. However, in the appendix I also show that point estimates are generally robust to using bandwidths of 2 to 10 points.[32] Standard errors are clustered at the attended school level.[33]

5 Validity

The main identifying assumption for the RDD is that the factors that affect students' performance vary smoothly around school cut-offs. Therefore, any subsequent discontinuity is the result of differences in school assignment. In this section, I discuss the evidence that supports this assumption.

Sorting. A first-order concern for any RDD is non-random sorting around cut-offs. This may occur if students are able to influence their school offer. In this setting, student manipulation of their offer is unlikely since they do not know their results on the placement exam at the time they submit their school preferences. To assess whether there was any institutional manipulation, I use the official algorithm instructions to replicate the observed assignment. I'm able to replicate school assignments for 98% of applicants.[34] In all of the subsequent analysis, I use the 'predicted' assignment from the replication rather than the actual assignment. Figure 2 shows a smooth density around the school threshold. Using the test suggested by Frandsen (2017), I do not reject the hypothesis that the density is smooth around the cut-off.[35] Overall, I do not find evidence of systematic manipulation around school admission cut-offs.

Selective Attrition. To interpret results causally, I need to rule out changes in the composition of students who complete the exams and the background questionnaire. Table 2 shows coefficients

[32] I use the term bandwidth to refer to the window around each cut-off. The data are not weighted differently according to the distance to the cut-off. Additionally, since the running variable is discrete and one cannot get infinitely close to the cut-off, I need to impose parametric assumptions (Lee and Card, 2008).

[33] Lee and Card (2008) suggest estimating standard errors clustered at the level of the discrete running variable to account for specification error. However, Kolesár and Rothe (2016) warn against clustering standard errors by the running variable when the running variable takes few distinct values. I opt for the most conservative approach.

[34] The main discrepancies appear to be related to: (i) manual allocation of students who chose a specific school that was left inaccessible because of a road closure, (ii) a very small number of students who were listed as 'special' cases (likely related to some disability) and appeared to be given priority into some schools, (iii) a small fraction of students who did not place in any school following the algorithm but who appear as placed in the SEP database.

[35] The test proposed by McCrary (2008) to check for manipulation in the forcing variable does not perform well when the forcing variable is discrete (Lee and Card, 2008).

from equation 1, where the dependent variable takes the value of one if the student cannot be matched to each respective dataset and zero otherwise.[36] I find no differential probability in completing the standardized tests in 5th and 6th grade (pre-assignment) nor completing the test in 7th grade (one year after assignment). I find that students who were offered a place in the morning shift are 3 percentage points more likely to attrit from the 8th grade standardized test sample (column (4)). I discuss the implications of this result in section 6.[37] I do not find statistically significant differences in attrition from the high school database sample within two years of the predicted graduation date. Because I allow for differential school progression across treatments, a different type of attrition arises from the fact that some questions in the background questionnaire do not appear every year (therefore, differentially missing answers for some respondents). I address this issue in two ways. First, I bound estimates for the questions affected by this issue using a trimming procedure (Lee, 2009).[38] Second, I correlate responses to these questions with pre-assignment characteristics and the set of outcomes for which I do have information. I discuss the results of these exercises in the corresponding results section.

Balance in pre-assignment characteristics. I test for smoothness in baseline characteristics for the final sample. Showing balance around the thresholds further reduces concerns about non-random attrition. Figures 3a - 3f plot the relationship between selected pre-assignment variables and distance to the cut-off and Table 3 reports coefficients estimated using equation 1. None of the variables change discontinuously at the threshold at standard significance levels. The results show balance for 5th and 6th grade standardized test results, gender, age, parental levels of education, living near the school, having siblings in the assigned school, living in a female-headed household, having a working mother, family size, having a disability, student's body mass index (BMI) and having attended a morning shift in primary school. Since some of the outcome variables are only available for either cohort, I show tests for discontinuity pooling both cohorts together and for the 2011 and 2012 cohorts separately. When estimating the equations jointly and performing a joint test for discontinuities, I fail to reject the null hypothesis of no

[36] Table A2 in the appendix shows these results by cohort.

[37] Since universal standardized testing stopped in 2014, I can only observe attrition patterns in 8th grade for the 2011 cohort for a single year.

[38] In order to make groups comparable, lower bounds are found by trimming the lower tail of the distribution of the variable of interest from the group of students who were assigned to the afternoon shift. Similarly, upper bounds are estimated by trimming the top of the distribution from that same group.

discontinuity. This lends support to the assumption of smoothness around thresholds.

6 Results

This section presents reduced form RDD estimates obtained from stacking between-school (within-facility) cut-offs. To interpret the results, I first discuss differences in the school environments that students experience. I then present the results for two outcomes that are commonly used to measure student achievement: results on standardized tests, which are administered and scored consistently across all students, and school-based academic outcomes, which are awarded at the school level. I then examine how students' perceptions, choices and behavior are affected by their school: I show results for non-cognitive outcomes, student behavior, educational aspirations and subsequent schooling choices.

6.1 Compliance with School Assignment & School Characteristics

Compliance. Figure 4a plots the results of a linear regression of a measure of matriculation compliance as a function of the score on the middle school placement exam. The x-axis is the distance to each school cut-off (normalized to zero) and the y-axis is an indicator variable taking the value of one if the student enrolled in the school predicted by the algorithm one year after the assignment took place. Matriculation to the assigned school is relatively high around the cut-offs. Approximately 65% of students who do not score above the morning school cut-off attend their assigned school (afternoon shift in their first-choice facility). However, there is also a clear jump in compliance if students are offered a place in the morning shift of their first-choice facility. Roughly 90% of children who get an offer of admission to their top-ranked school comply. One potential reason for imperfect compliance is time of day preferences: Figure 4b shows that roughly 30% of the students assigned to the afternoon shift enroll in the morning shift of a different facility. Table 4 formalizes these relationships. An offer to the morning shift increases the likelihood of enrollment in the assigned school by 20 percentage points (column (1)). While 9% of students with afternoon offers manage to enroll in the morning shift of their first-choice facility, scoring right above the cut-off increases the likelihood of enrollment in the

morning shift by 80 percentage points (column (2)) and enrollment in any morning shift school by 68 percentage points (column (3)).

School Environments. In what ways are morning shifts systematically different? I discuss two key sources of differences in school environments: peer characteristics and school personnel.[39] Students who barely score above the admission cut-off experience schools with higher average peer academic performance.[40] Column (1) in Table 5 shows the coefficient of a regression of the average peer placement score on an indicator for whether the score in the placement exam was above the cut-off. There is a significant jump of 0.6 s.d. in the mean peer placement scores experienced by students. Appendix Table A3 column (2) reports this discontinuity using the average peer results from the 6th grade standardized test. The coefficient is still large at 0.4 s.d. and statistically significant. Figures 5a and 5b show a graphical representation of these discontinuities.[41]

Relative to other papers in the literature that look at differences in school quality as proxied by peer scores, these jumps are relatively large. For instance Pop-Eleches and Urquiola (2013) document peer score jumps of 0.1 s.d. in their study of high school quality in Romania and Kirabo Jackson (2010) of 0.2 s.d. in Trinidad and Tobago. A potential factor creating larger average differences in academic performance across shifts is the fact that students who prefer to attend afternoon shifts have significantly lower scores relative to those who prefer morning shifts (an average difference of 0.47 s.d.).[42]

I also document discontinuities in school-level averages of other covariates that are correlated with student achievement. A morning shift offer leads to exposure to peers whose family characteristics reflect a higher socio-economic status (SES), as proxied by household ownership of durable assets (Table A3 in the appendix, column (3)).[43] Likewise, on average, classmates'

[39] While it is possible for teachers to teach both in the morning and afternoon shifts of a given facility, in most cases each shift employs a different set of teachers.

[40] Schools refer to the school-cohort to which the student is exposed.

[41] Had students perfectly complied with their assigned allocation, the corresponding average difference in peer scores would have been larger in magnitude: a jump of 1 full s.d. (Table A3 in the appendix, column (1)).

[42] As discussed in Section 4, I exclude students with afternoon preferences from the RDD estimation because they do not compete for morning slots. However, they do compete for afternoon slots with those students who do not place in the morning shift. If the afternoon shift is not oversubscribed, they would also be able to enroll regardless of their score.

[43] A limitation of the SES index, which is a principal component constructed with questions about household ownership of assets, is that it is constructed using data from the high school background questionnaire rather than the assignment dataset. However, it is unlikely that assignment affected ownership of durable assets, and indeed

parents are 9 percentage points more likely to have education beyond middle school (columns (4)-(5)).

Figures 5c to 5f show discontinuities in the average characteristics of the school personnel. First I look at personnel qualifications. Despite mixed evidence on the role of teacher academic credentials on student achievement (e.g. Clark et al., 2009; Clotfelter et al., 2010; Harris and Sass, 2011), many education ministries (including the SEP) encourage teachers to obtain advanced degrees. However, the overall fraction of teachers who report having a graduate degree is small. The discontinuity at the school level for those who barely placed in the morning shift is negative (Table 5 column (3)) but statistically insignificant. However, there is a significant increase of 8 percentage points in the fraction of principals who have a graduate degree (column (4)).

A second difference in teacher characteristics is whether they voluntarily enrolled in a nation-wide teacher incentive program. The program rewarded teachers with salary bonuses based on a number of criteria, including seniority, educational attainment, teacher performance and some measures of student achievement.[44] Students who barely score above the admission threshold are exposed to school environments in which the share of teachers enrolled in the program is 7 percentage points higher (Table 5 column (2)).

The quantity of teachers relative to students may also be important. A large literature has reviewed the impacts of class size on student achievement, usually finding no effects or a negative effect on student achievement (Krueger, 1999; Angrist and Lavy, 1999; Urquiola, 2006; Fredriksson et al., 2012). Similar to other contexts (e.g. Abdulkadiroğlu et al., 2014), I find that students who obtain an offer of admission to the more competitive morning schools are exposed to a lower teacher-student ratio (column (5)). The effect is small but statistically significant, suggesting that students with morning shift offers attend larger schools and classes (on average a difference of 4.8 additional students per teacher at the school level). This result is likely driven by the higher demand for morning school seats, which leads to a larger number of incoming students. I explore the extent to which this feature may negatively affect students in section 7. Finally, I do not find statistically significant differences in ad-hoc parental expenditures (e.g.,

I do not find that it varies at the discontinuity at the student level.

[44]This program is the now defunct *Carrera Magisterial*. There are very few studies of its impact, though a review of the program found very small effects at the middle school level (Santibañez et al., 2007).

uniforms, unofficial fees, etc.) across schools (column (6)).

6.2 Measures of Learning: Standardized Tests

I now turn to learning outcomes. I start by examining whether attending better schools results in higher academic performance as measured by standardized test scores. These tests are applied and graded in the same way across all test takers, and therefore are not affected by students' relative position in the academic distribution. I show two types of results: the results for the low-stakes exam that students take at the end of 7th grade and of the high school entrance exam completed at the end of 9th grade.

Low-Stakes 7th Grade Tests. Section 5 showed no differential attrition in the completion of the 7th grade standardized test. Therefore, I directly compare the results of students at the margin of admission. Throughout, I show results for the math and language sections of the exam separately. Table 6 shows that students who scored above the admission threshold have a statistically significant increase in language scores (Spanish) of 0.06 s.d.. This difference is robust to the inclusion of controls. In comparison, the effect for math is smaller (0.01 s.d.) and statistically insignificant. Figure A8 in the appendix shows the coefficients for these results for a range of different bandwidths. Overall, the magnitude of coefficients is similar, with insignificant effects for math and positive and significant effects for Spanish (insignificant at the 10 percent level when the bandwidth is restricted to less than 3 points from the cut-off).[45]

High School Entrance Exam. Next, I estimate the effects of the morning offer on the results of the high school placement exam completed in 9th grade. From the point of view of the student, this is a high stakes exam that will determine the high school they will attend. First, I find no significant differences in the probability of taking the exam (appendix Table A5 columns (1) and (2) and Figure A2a).[46] Table 7 columns (1) and (2) show the results for the sections of the exam that tested math and Spanish. I estimate gains of approximately 0.04 s.d. for Spanish

[45] In section 5, I showed that standardized results for 8th grade (only available for the 2011 cohort) are affected by differential attrition. I show bounded estimates for 8th grade in appendix Table A4. The raw coefficients (without accounting for selection) for Spanish are positive but noisier and insignificant. For math, the point estimates are negative. Since the bounds are fairly wide, and both contain zero, overall it is difficult to establish the effects in the 8th grade standardized test.

[46] Students can register for the exam early in the year and then decide not to take it later in June. Approximately 2% of all students fall into this category.

(significant at the 10 percent level). The magnitude and significance of the results appear to be robust to a range of bandwidths (Figure A9c in the appendix). The coefficient for math is zero (columns (3) and (4)). These effects are shown graphically in Figures 7a and 7b.[47]

Heterogeneous Effects on Learning Measures. The results from both standardized exams suggest that an offer to a better school led to small but significant gains in language scores.[48] Recent empirical work has highlighted the importance of specific school and individual characteristics in explaining whether better schools affect learning (e.g. Shi (2016); Hoekstra et al. (2016)). I exploit the fact that I observe students' background characteristics, and that I have variation in school cut-offs, to estimate heterogeneous treatment effects. Figures 8a and 8b plot point estimates and confidence intervals for different ranges of school cut-offs. I cannot reject the possibility that the effects on Spanish standardized scores for students in less selective facilities (those at the bottom quartile of entrance cut-off scores) are different from zero.[49] At the individual level, I explore differences by gender, previous academic achievement and parental education. I do not find consistent differences in learning by gender (Table 8 Panel A). An important question is whether more disadvantaged students (as proxied by parental education and low pre-treatment academic performance) are less likely to benefit from placing in better schools because the level of instruction might be too high for them. For instance, proponents of the "mismatch" hypothesis contend that students may be adversely affected if they attend schools where their academic level is much lower than that of their classmates. Table 8 Panel B shows heterogeneous results by previous performance on the 6th grade standardized test and Panel C heterogeneous results by whether the students' mothers completed middle school or less. At least for this set of outcomes, I do not find that more disadvantaged students gain less from better school environments. The point estimates suggest that the effects are concentrated on disadvantaged students, but becuase they are noisy, I canot rule out that they are the same, except for gains in math performance on the 9th grade. Those with below-median academic performance experience average gains of gains 0.08 s.d. (gains of 0.04 s.d. for students whose

[47] When looking at the results across all tested subjects, I do not find that the effects are significant (Table A5 in the appendix, columns (3) and (4)).

[48] This results joins others in the literature that have found small but positive impacts from attending better schools on test scores (e.g. Pop-Eleches and Urquiola (2013), Kirabo Jackson (2010)) and contrast with the null results from other contexts (Lucas and Mbiti, 2014; Abdulkadiroğlu et al., 2014; Duflo et al., 2011).

[49] Figure A3 in the appendix shows these results for math.

mother did not complete education beyond middle school).[50]

6.3 School-based Assessments

GPA. Grades are the tool used most widely to assess performance at school. They serve the double function of providing students with feedback and serving as a yardstick to compare them. However, GPA comparisons across schools may also reflect differences in school standards and teacher discretion rather than just academic ability. Nonetheless, even when academic ability is held constant, grades may matter because they may act as signals in the labor market, within the education system or to students.[51] A clear example in this context is the fact that elite high schools have strict minimum middle school GPA requirements for admission. Similarly, grades may motivate or discourage students or serve as a signal about their ability, which may affect later schooling decisions (Bobba and Frisancho, 2016; Azmat and Iriberri, 2010; Papay et al., 2016).

Figures 10a and 10b and Panel A in Table 9 show the effects on 8th grade Spanish and math GPA (the scale is out of 10 points).[52] Students who get an offer for a morning shift obtain 0.2 point lower GPAs than their counterparts who do not (corresponding to a decrease of 0.14 s.d.).[53] While there is no official policy of'grading-on-a-curve' (which is broadly confirmed by Figure 9a, which shows differences in the distribution of GPAs by shift), this result could still suggest that teachers implicitly use other students as a reference when assigning grades. Alternatively, grading standards may be higher in morning shifts (despite having the same curriculum) or GPAs may capture other dimensions of student effort or behavior that standardized tests do not (e.g. attendance, participation, etc). In Section 6.6, I explore potential mechanisms and find no evidence of increased student truancy, which may suggest that these effects are driven by teacher

[50] I also detect small but negative effects for students who are above the median in pre-assignment performance in math. Abdulkadiroğlu et al. (2014) also detects small negative effects in math from attending elite schools.

[51] Recent empirical work has found long-term effects from teacher discretion in assigning scores even when performance was the same (Diamond and Persson, 2016; Lavy and Sand, 2015).

[52] These are self-reported measures of 8th grade GPA. Students do not have GPA information for 9th grade by the time they complete the background questionnaire. I can also look at administrative records for 9th grade middle school GPA. However, as will be shown, there is a differential likelihood of getting the certificate, so selective attrition is a concern. Regardless, the point estimates for that measure are similar to those obtained from self-reported data.

[53] An offer to a more competitive middle school also increases the probability of having a grade below 7 (the minimum required GPA for admission to an elite high school) by 2 percentage points. However, this result refers to 8th grade GPA only, not to the entire middle school GPA, which is the relevant criterion for elite school admission.

behavior.

Grade Progression and Middle School Certificate. A related outcome, which depends on passing core courses, is timely progression through school and the probability of obtaining a middle school certificate. I find that scoring above the cut-off increases the likelihood of failing at least one class during the previous year by 4 percentage points, corresponding to a 17% increase (Table 9 columns (7) and (8) and corresponding Figure 10c). Students are also 3 percentage points more likely to repeat grades, as evidenced by the differential likelihood of completing the universal standardized tests in their predicted grade (Table 2 column (4) and (5)).[54] I corroborate this result by matching students in the 2012 cohort to an alternative data set containing the results for a different exam that was implemented with a random sample of 9th grade students in 2015.[55] I also find a higher likelihood of attriting from this data set for students with offers to more competitive schools (Appendix Table A6 column (1)).

Many countries have 'no failing' policies at the basic education level to ensure the timely progression of students. In Mexico, school progression at the middle school level is not guaranteed and students are required to obtain a minimum passing score in core courses in order to complete middle school. I examine the impacts on the likelihood of obtaining a middle school certificate using the administrative records linked to high school applicants. I find that an offer to a more competitive school results in a 1 percentage point decrease in the probability of obtaining a middle school certificate within two years of the predicted graduation date (Table 9 columns (9) and (10)). This corresponds to a 25% decrease in the probability of obtaining a middle school certificate. The results are generally robust to the window choice around the cut-offs (Figure A10e in the appendix). While not obtaining a certificate on time implies that students will not be able to enroll in high school the following academic year, it does not necessarily imply that they will fail to obtain a certificate at all. For instance, students may repeat 9th grade or may take make-up exams until they pass all their courses and are able to graduate.[56] Unfortunately, the

[54] The magnitudes of school repetition are similar to those estimated from attending competitive high schools (Ortega Hesles, 2015). Dustan et al. (2016) also infer enrollment in school from completion of the universal standardized exam.

[55] Details on that exam (PLANEA) are noted in the data appendix. This exam, which started in 2014-2015, replaced the previous universal standardized test, but it is only implemented with a sample of students. Overall, I match 25% of students in the sample. I do not have access to the results of the test, only to whether students completed it.

[56] For instance, Jacob and Lefgren (2009) find that early retention does not affect the likelihood of high school

local office of the SEP does not keep data on whether students end up obtaining these certificates. However, they can access information on whether their report cards still mark any of the core courses with a failing grade. I construct a dummy variable with value of one if the student has at least one failed core subject in 9th grade 3 or 4 years after predicted graduation date. Table 9 columns (11) and (12) show that while the fraction of students who do not have a certificate (as proxied by this measure) falls by half, there is still a 1 percentage point difference in the probability of having successfully completed all core courses.[57] Overall, these results suggest that attending a better school may negatively affect students' ability to graduate from middle school, which has been shown to be highly correlated with worse labor market outcomes: 90% of Mexico City residents with incomplete middle school are employed in low-quality manual labor jobs (Blanco et al., 2014).

Heterogeneous Effects on School Assessments. Table 10 shows heterogeneous effects for GPA, the likelihood of failing at least one class and both measures of completing middle school. I find that males are more adversely affected than females (Panel A). Males who scored above the cut-off have a 0.26 point lower GPA relative to those who got an offer for an afternoon shift, whereas for females, the GPA is 0.16 points lower. The pattern holds for failing a class, but I cannot reject the equality of coefficients. The impact on failing to obtain a certificate for females is half of that for males, but the coefficients are noisier. I do not find consistent evidence that students with less educated parents or students who obtained lower standardized scores in primary school are more affected. Figure A4 in the appendix shows the results by school cut-offs. Overall, students appear to be similarly affected by these patterns regardless of school selectivity.[58]

6.4 Perceptions of Relative Position, Psychology and Aspirations

Next, I look at differences in students' self-reported measures of their relative ability, perseverance, time management and aspirations. The measures are constructed using self-reported data from the background questionnaire, and are presented using thematic indices that group related

completion in the US, but it does for those in higher grades.

[57] It is possible that students might obtain the certificate through other systems (e.g., adult education, etc.) which would not be captured in their school records.

[58] Albeit those in more selective schools are more likely to complete all their core courses.

questions (which increases statistical power and reduces the likelihood of spuriously finding significance for any one individual component).[59] All indexes are constructed by averaging over individual variables and normalizing variables by their standard deviations.[60]

Figures 11a - 11d show the relationship between each of these measures and the distance in placement score to the cut-off. Table 11 shows the estimated regression coefficients. Columns (1) and (2) confirm that students have a negative perception of their relative academic ability. The coefficient for the 'relative index' was constructed based on students' reports of their relative academic performance on different subjects. Students who barely scored above the morning-shift admission cut-off are more likely (0.2 standard deviations) to report feeling that their academic performance is worse than that of their peers. The result holds for each one of the components of the index: they feel worse than their peers in history, Spanish, biology and mathematics. The estimated coefficient for math is double in magnitude and statistically different from the rest of the other courses. Columns (3) and (4) report the causal impacts of scoring above the cut-off on an abbreviated index constructed from four questions used to measure perseverance.[61] I find that the offer to a morning shift lowers the perseverance index by 0.10 standard deviations. The relative performance and the perseverance questions are only asked in the 2014 version of the high school background questionnaire (the predicted graduation year for the 2011 cohort). Because I show that students get differentially delayed by treatment status, one concern is that these results are affected by differential question completion. Therefore, I construct trimmed bounds for these estimates (as described in section 5). In both cases, upper and lower bounds support the conclusion that placing in a better school has negative impacts on self-reported measures of relative ability and perseverance. It is worth noting that differential

[59] The 'relative index' was constructed from a question that asked students how they felt their academic performance was relative to their classmates in history, biology, math and Spanish. Answer values range from -1 to 1, with negative values if they thought they were worse and positive if they felt they performed better than their peers. The 'perseverance index' is an abbreviated version of the traditional grit scale, which includes questions on whether students agreed or disagreed with a list of statements: (i) I finish what I start, (ii) Setbacks discourage me, (iii) I am a diligent person, (iv) I am a hard worker. In 2015 students were asked another set of questions about their ability to manage their time and prioritize work to achieve objectives. This included questions on the frequency in which they would: (i) establish priorities, (ii) finish what they started, (iii) establish deadlines and (iv) plan their work. I refer to the combination of these questions as the 'time management index'.

[60] Coefficients calculated using average effect sizes (AES) as per Kling et al. (2004) and Clingingsmith et al. (2009), which account for covariance across estimates, are very similar.

[61] These questions are also commonly used to measure grit, which is a measure that combines perseverance and passion (Duckworth et al., 2007).

question completion is likely to underestimate the true impacts. Since I can observe the pre-assignment characteristics of students who are delayed, as well as their outcomes (measured in the 2015 version of the questionnaire) I can rule out the possibility that it is the top students who are delaying high school entrance for a year.[62] Students who are delayed have lower grades in primary school, a lower middle school GPA and are less likely to obtain a middle school certificate (Table A8 in the appendix). The 2015 version of the questionnaire asked students a different set of questions that I use to construct an index of their ability to manage their time to achieve goals. The regression results for the 'time management index' created from those questions (with corresponding bounds) for the 2012 cohort are shown in columns (5) and (6). Again, an offer to a better school has a negative impact (0.07 standard deviations, significant at the 5% level) on students' reported ability to prioritize and complete tasks. The bounded estimates support these results (the lower bound coefficient is negative but not statistically significant).[63]

Columns (7) and (8) show that those who are barely admitted to a morning shift are 2 percentage points less likely to aspire to attend college or earn a post-graduate degree, with a corresponding increase in their aspiration to obtain a technical (non-college) degree, shown in columns (9) and (10). A large proportion of students aspire to obtain a college and/or a graduate degree (87% of students), so this is a margin where it might be difficult to detect adjustments. The coefficients are of similar magnitude for different bandwidth choices, but noisier and statistically insignificant for narrow bandwidths (Appendix Figure A11).

6.5 High School Track Choices

Declines in self-reported measures of non-cognitive skills may be driven by 'reference' bias rather than by an actual change in non-cognitive measures (West et al., 2016; Dobbie and Fryer Jr, 2013). However, even if schools do not, per se, change these traits, the ways students perceive themselves may have real consequences through dynamic complementarities: perceptions about

[62] To the extent that motivation and perseverance are positively correlated with academic outcomes, which holds in the data, this would suggest that raw estimates would underestimate the true effects.

[63] The questions used to construct this index asked to report how frequently students undertook certain actions, instead of asking them to assess to what extent statements described them. Reporting a frequency may be less likely to be influenced by external frames of reference.

how they compare to others may matter for subsequent schooling decisions.[64] In this setting, I have a revealed preference measure of schooling decisions: I can observe the types of high school tracks that students apply for. Students who are offered a seat in the morning shift are more likely to choose vocational high school tracks (as opposed to academic) at the end of middle school.[65] Table 12 and Figure 12 show a 1 percentage point increase (approximately 5%) in the share of vocational track choices in students' high school portfolios for those who scored above the cut-off.[66]

Heterogeneity in Non-Cognitive Skills and School Choices. Table 13 shows heterogeneous results for non-cognitive, aspiration and track choice measures. I do not find significant differences by gender in college aspiration or in the fraction of vocational schools that students choose. Females appear to be more affected in measures of perseverance and time management, but the coefficients are insignificant. I find that those most affected in the perseverance index are students who were performing better in primary school and whose mothers have higher levels of education. This might suggest that it is those who are surprised by obtaining worse signals about their performance who might be most affected. Finally, the negative effects on college aspirations are concentrated on students whose parents have lower levels of education.

6.6 Behavior Changes

Parents and students' behavior might endogenously respond to the quality of schools (Pop-Eleches and Urquiola, 2013; Todd and Wolpin, 2003) or students' relative positions, which could in turn affect their grades and likelihood of completing middle school. For instance, students

[64] Previous research focused on high school application behavior found that if students assign a zero probability to being matched to one of their choices, they might drop it altogether (Chen et al., 2015). Bobba and Frisancho (2016) find that students who had taken a mock exam and received positive feedback about their performance were more likely to increase the share of academic programs they listed. On average, there was no effect for those who received negative feedback. However, they find a negative effect for students who got negative feedback and who resided in areas in which schools had higher academic requirements. Their interpretation is that students learn about own ability, which affects preferences for programs.

[65] These choices may also reflect a reduction in overconfidence: for high school drop-outs, technical degrees might have higher returns than the academic alternatives (Ferreyra et al., 2017).

[66] Officially, there are three high school tracks: technical, general and vocational. I denote the general track as 'academic' and combine technical and vocational tracks into a single category denoted 'vocational'. I exclude IPN elite high schools from the technical category though officially they fall within that type, as more academically oriented students are more likely to apply for those seats. Figure A6 shows that GPA is negatively correlated with vocational/technical school, but not for the elite technical school in the city (IPN). In Appendix B, I discuss coding choices in detail.

might misbehave if they feel that they perform worse than their peers, or parents might invest less in their children's education if they perceive them to be less academically inclined (Dizon-Ross, 2016; Kinsler et al., 2014). In this section, I explore whether students, parents and peers behave differently. I do not find systematic evidence of changes in behavior.

Students. Table 14 Panel A, shows self-reported measures of student truancy and time spent in school/out-school activities. I do not find any consistent evidence of increases in the likelihood of skipping school or a class for those who score above the cut-off (columns (1) and (2)). If anything, the offer to the morning school increases their likelihood of reporting that they have never skipped class by 1 percentage point (significant at the 10 percent level). I also do not find significant differences in students' preparation for the high school entrance exam (column (3)), nor I find that they are more likely to work (column (4)).[67]

Parents. Panel B reports on an 'adult monitoring' index that was constructed from students' answers about the frequency with which their parents monitored their attendance, grades and homework. Since the questions are only asked in the 2014 version of the questionnaire, I show bounded estimates. The raw coefficient is very small and insignificant, but the bounds are too wide to be informative. Therefore, I use a different measure of parental investment: whether students report enrolling in a private preparation course for the high school exam (which parents would have had to pay for). While private courses are relatively common, I do not find evidence of differential effects on this variable (column (6)).

Peers. Students might be socially marginalized by their peers if they place in the bottom of the ability distribution (Pop-Eleches and Urquiola, 2013). In this context, I do not find that students are more likely to be bullied if they score above the cut-off threshold (Panel C).

Finally, I do not find systematic differences by gender, parental education or performance in primary school, except for a decreased likelihood that females will skip class if they get an offer to better schools (Table A9 in the appendix).[68]

[67] The question about preparing for the exam is proxied by whether they report never having practiced a multiple-choice exam before. This question only appeared in the 2014 and 2015 version of the questionnaire, so I restrict the analysis to the 2011 cohort.

[68] This is in line with the effects reported in other contexts (e.g., Dasgupta et al. (2017)).

7 Alternative Interpretations

The results in the previous section showed that students who were barely admitted into better schools have, on average, lower GPAs, are less likely to obtain their middle school certificate on time, have lower scores in measures of time management and perseverance and are more likely to choose vocational high school programs. These findings are consistent with the hypothesis that placing into a better school can affect students through a worse placement in the ability distribution. In this section, I examine whether students are negatively affected by other school characteristics.

Class size. An offer to a morning school increases the probability of attending a school with a higher number of students per teacher. One possibility is that this feature negatively affected students (although this scenario is harder to reconcile with the measured gains on standardized tests). Since there are hundreds of schools in the sample, I can explore the cross-sectional correlation between class size and students' outcomes. Table A10 in the appendix shows heterogeneity by differences in teacher-student ratio within a facility for selected variables. None of the interactions are statistically significant, though the estimates are noisy. Figure A7 plots the RDD coefficients estimated for each facility against the teacher-student ratio gap. The figures do not suggest strong associations between larger teacher-student gaps and worse student outcomes. Overall, I do not find compelling evidence supporting the hypothesis that class size is the main driver of the estimated effects.

Time of day. Recent empirical work has shown that starting school at a later time can improve student performance, since adolescents may benefit from more hours of sleep and later wake-up times (Carrell et al., 2011).[69] One possibility is that early morning shifts negatively affect students' grades and their school progression. Motivated by this possibility, I use the cut-offs generated between afternoon shifts at students' first-choice facility and any other school placement.[70] In the analysis so far, I have not used this source of additional variation for two

[69] However, other work has found that students learn more in the morning (Pope, 2016). While in this context, this could partly explain the gains in Spanish, it does not fully explain the heterogeneous effects by school competitiveness.

[70] Recall that the assignment algorithm attempts to allocate students to a second- and then a third-choice facility or to another facility nearby if the first choice afternoon shift is also full. This creates a different set of potential school cut-offs that could be exploited in an RDD.

reasons. First, focusing on morning vs. afternoon shifts facilitates the interpretation of estimates because the facilities are kept constant. Second, I find some evidence to suggest that estimates might be affected by different patterns of attrition for students around facility cut-offs (Panel C and D in Table A2 in the appendix). Placing in a first-choice facility *decreases* the likelihood of attrition by 3 percentage points (column (3)). In other words, those who are not offered their first-choice facility are more likely to not take the universal standardized test a year after middle school placement.[71] This effect does not appear to be completely driven by delays in enrollment, as a differential effect still persists two years later. However, by the time students take the high school exam in the 9th grade, this difference has largely disappeared. Because one potential interpretation of these patterns is that the initial gains in retention from placing in a preferred facility are offset by a subsequent higher likelihood of attrition (of similar magnitude) from more selective schools, one concern is the changing composition of students in this sample.

Nevertheless, I estimate the effects of attending 'better' schools, as proxied by peers' scores, using across-facilities cut-offs. These effects are estimated for the sample of students who attend facilities with oversubscribed afternoon shifts.[72] Selected results are shown in appendix Table A11. First, as expected, students who barely get an offer for their first-choice facility are less likely to attend a morning shift (column (1)). The mean score of their peers is 0.4 s.d. higher than that of their next school option (column (2)), suggesting that on average the afternoon shift of a first-choice facility is still a better schools relative to the next choice. The overall effect on the high school exam is statistically insignificant (column (3)). However, the pattern of results for school-based assessments is similar to the results calculated using within-facility discontinuities. Students have lower GPAs and are more likely to fail a course if they barely score above the facility cut-off on the placement exam. The magnitude, however, is much smaller. The effects on obtaining a certificate are positive but very small and statistically insignificant. However, I do find that students above the cut-off have lower measures of perseverance and are more likely to think that their academic performance is worse than that of their peers. I do not find differences in their college aspirations and high school choices. While caveats remain, these results

[71] This dataset contains the universe of public and private schools, so this does not indicate that students have moved to private options.

[72] These estimates only apply to facilities that are in very high demand, which might be less representative of other schools.

suggest that time of day is not a primary factor explaining students' negative performance on school-based assessments.

8 Discussion

Evaluating different dimensions of students' school experiences is central to our understanding of the returns to school quality and the ways human capital is formed. In this paper, I exploit the algorithm that assigns students to middle schools in Mexico City to better understand the trade-offs that students face when choosing schools of different quality. I use several sources of administrative data to study implications for standardized test scores, school-level measures of achievement, non-cognitive skills and high-school track choices.

I find gains in human capital. An offer to the more selective morning shift has small but positive effects on students' Spanish standardized test scores. However, students' school-based performance is worse relative to those who barely place in less selective schools. This appears to have important consequences for their labor market trajectories: on average, students who get an offer to the more selective morning shift are 25% less likely to obtain a middle school certificate within two years of their predicted graduation date. This finding suggests possible inefficiencies in the way middle school certificates are awarded, as individuals of similar (or higher) academic ability have different probabilities of completing grades and graduating from middle school.

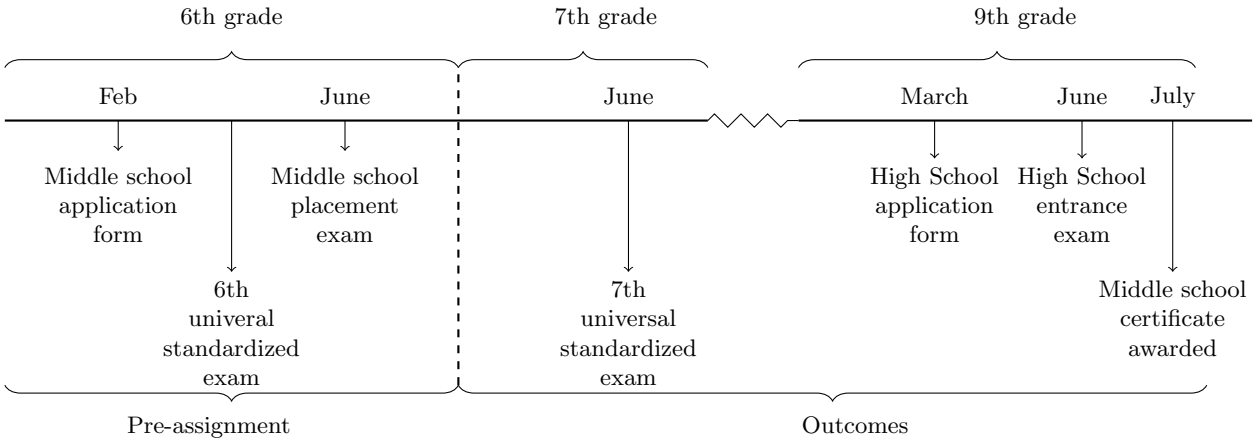
In addition, students in better schools feel worse than their peers, have lower scores in measures of perseverance and their ability to prioritize and complete tasks and are less likely to aspire to attend college. These reduced-form effects suggest that negative frames of reference might be sufficiently important to overwhelm the potential non-cognitive benefits from pooling with high-achieving peers. While I cannot speak to the question of persistence nor to how these effects might change as students form new reference groups, I provide evidence of a potential channel through which self-perceptions might affect long-term outcomes: how individuals make decisions about future educational investments. At the end of the 9th grade, students who were barely admitted into a better school are more likely to apply for vocational rather than academic high school tracks.

One limitation of this study is that I cannot fully disentangle the causal chain that explains these results. For instance, it is possible that students who obtain lower grades may infer that they are not academically inclined and perceive higher marginal costs from investing in academic choices (on the flip-side, those who obtain higher grades in the afternoon shift could be positively updating about their absolute ability). Another possibility is that the realization that they are worse at school affects their school performance and lowers their probability of graduating.

These results have a number of implications. First, there are several settings in which marginal students might be encouraged to attend a better school (e.g., voucher programs, affirmative action policies, etc.). Policymakers might want to experiment with interventions that could either motivate or provide students with broader frames of reference. A number of recent studies in other contexts have found positive effects from interventions aimed at strengthening positive identities and reaffirmations of personal adequacy (Lavecchia et al., 2016). Second, school-choice policies usually assume that parental demand for high-achieving schools will improve market-level outcomes. How much parents consider dimensions other than academic achievement is an open question that has important implications for education markets. However, the results show that some students might be negatively affected in school environments that might have been considered better ex-ante. Finally, policymakers should be careful when using school-based assessments to evaluate students in competitive processes, as well as when creating systems that might 'lock' students into long-term educational pathways.

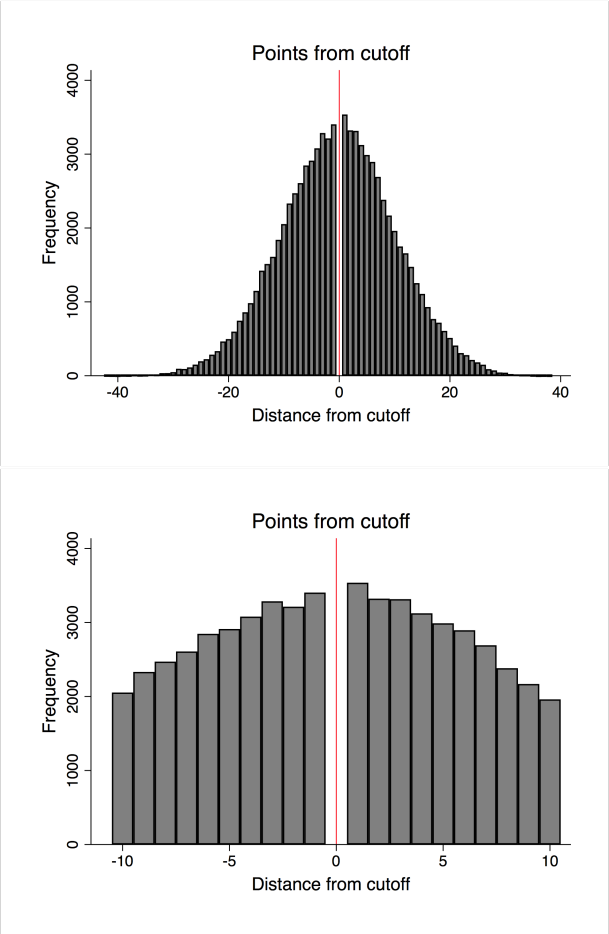
9 Figures

Figure 1: Timeline



Notes: This timeline shows the timing when different events and data collected took place. Academic years in Mexico run from August to July. Every January/February students in 6th grade complete an application form for middle school in which they list their facility preferences. The middle school placement exam is taken in May or June of that same year. The running variable in this study is constructed based on the results of that exam. The universal standardized tests, which stopped in 2014, were applied nation-wide to all primary and middle school students in June of each academic year. I use these tests to measure achievement at the end of 7th grade, enrollment in 7th and 8th grade and baseline achievement in 5th and 6th grades. Registration for the high school placement exam takes place in February of 9th grade and the corresponding exam takes place later in June. Middle school certificates are awarded at the end of the school year (around July).

Figure 2: School Density

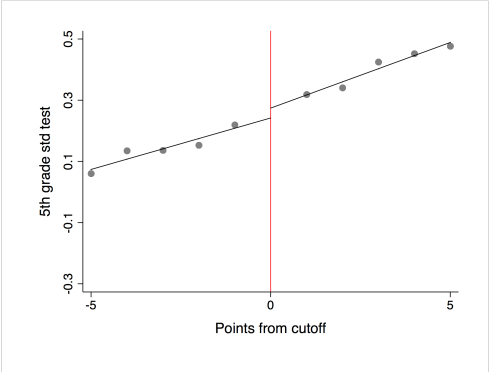


	Frandsen Test			
Curvature Allowed (k)	0.01	0.02	0.03	0.04
Hypothesis testing p-value	0.10	0.37	0.73	0.94

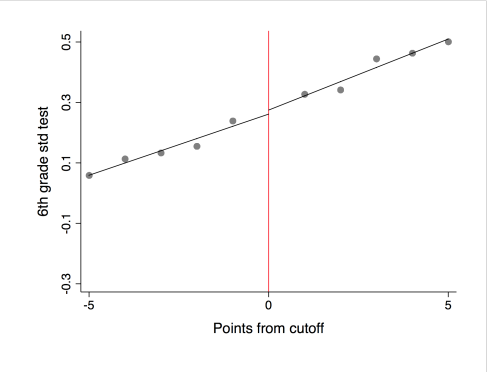
Notes: These figures show the distribution of the running variable in the RDD (the distance in points to the cut-off score for their first choice school). A Frandsen test for manipulation was performed for several choices of k, where k determines the maximal degree of non-linearity that is still considered to be compatible with the hypothesis of no manipulation.

Figure 3: Smoothness in Pre-Assignment Characteristics

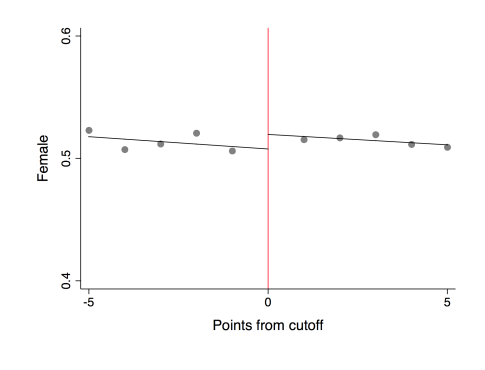
(a) 5th Grade Standardized Test



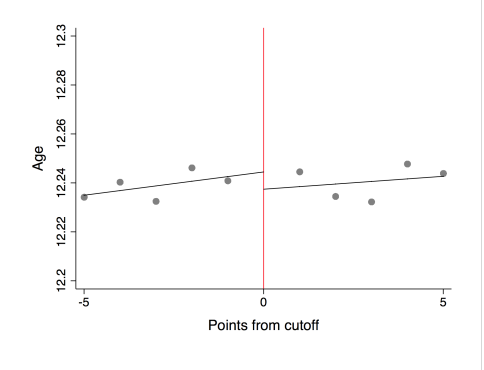
(b) 6th Grade Standardized Test



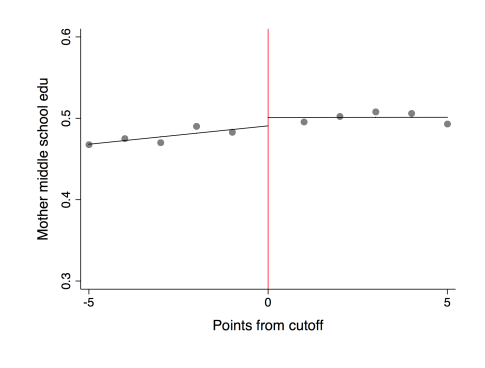
(c) Female



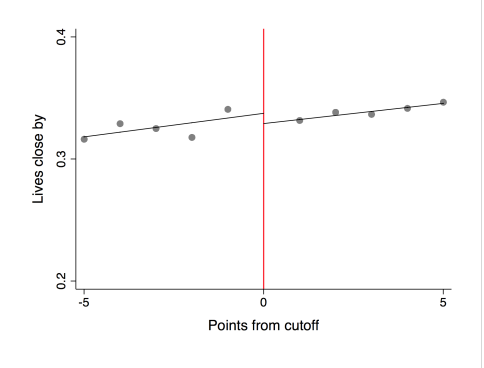
(d) Age



(e) Mother has more than Middle School



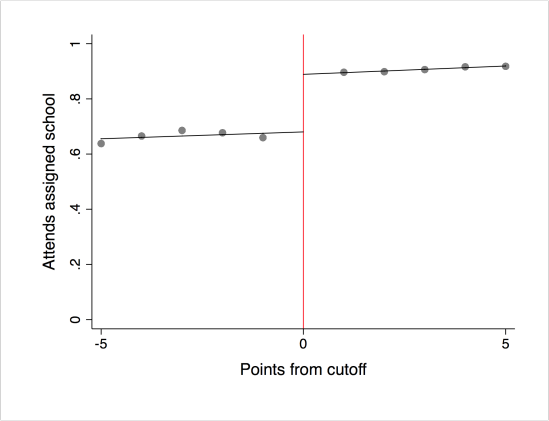
(f) Lives Near School



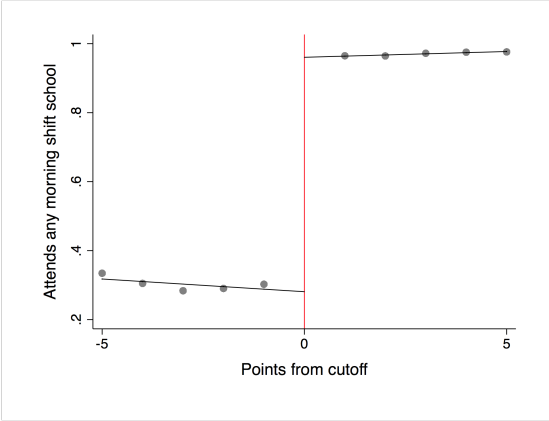
Notes: The figures plot the mean value of each pre-assignment variable for each placement score bin. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. All school cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 4: Compliance with School Assignment

(a) Matriculation to Assigned School



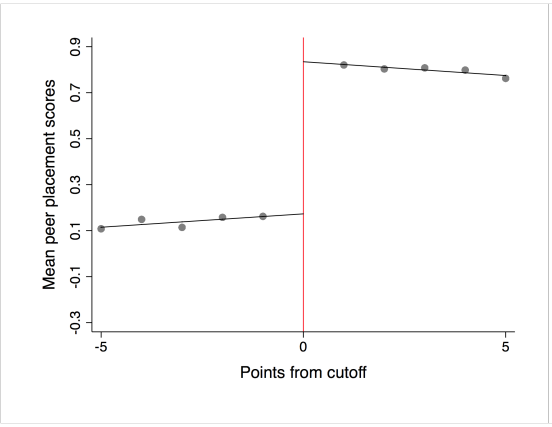
(b) Matriculation to Any Morning Shift



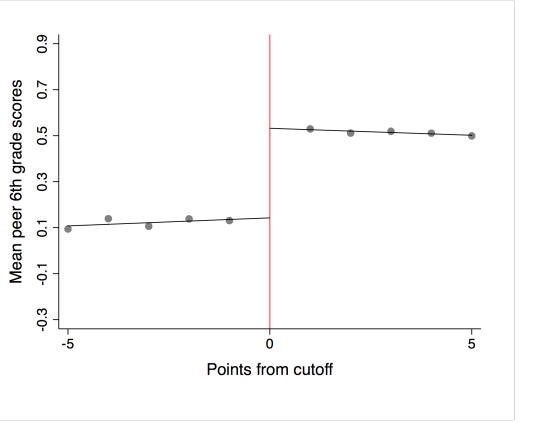
Notes: The figures above plot the mean value of: (a) matriculation to the school predicted by the assignment algorithm and (b) matriculation in any morning shift school, for each placement score bin. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. All school cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 5: School Characteristics: Peers and Personnel

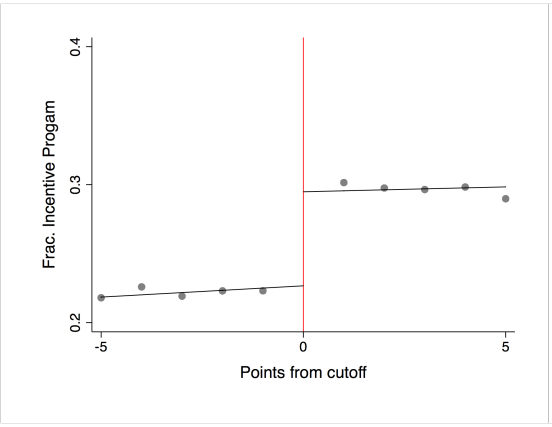
(a) Peers' Average Placement Score



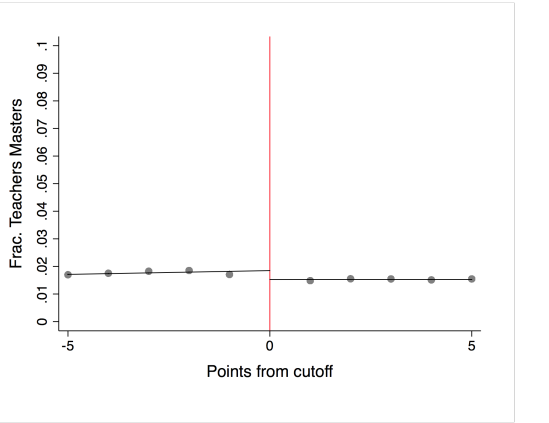
(b) Peers' Average 6th Grade Standardized Scores



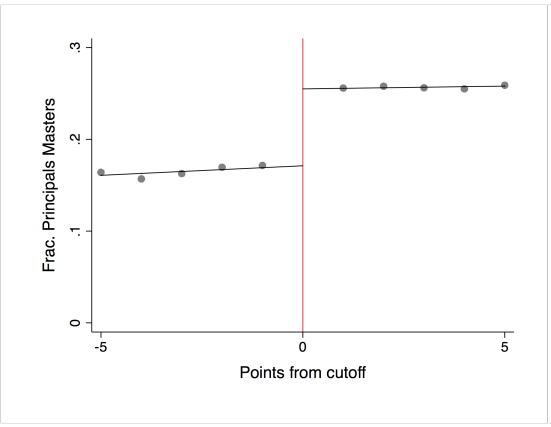
(c) Fraction of Teachers in Incentive Program



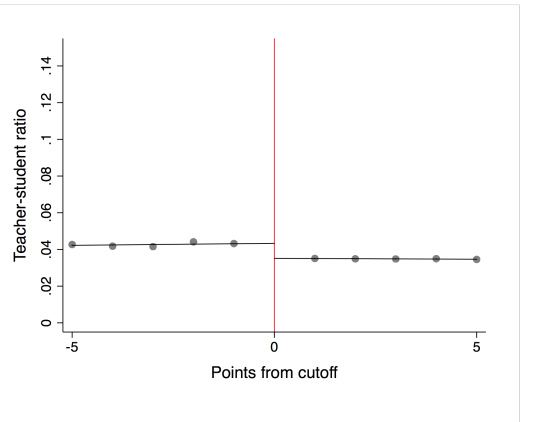
(d) Fraction of Teachers with Masters degrees



(e) Fraction of Principals with Masters degrees



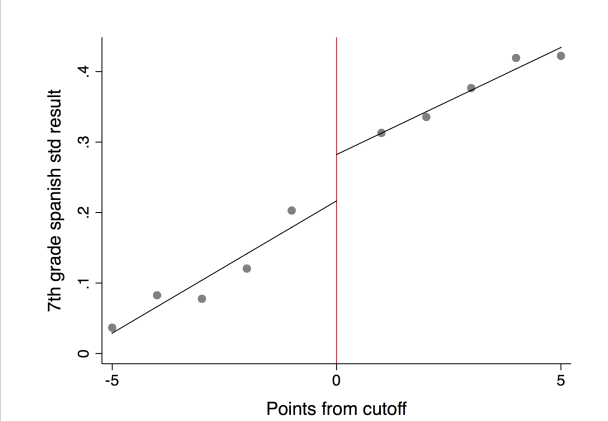
(f) Teacher-student ratio



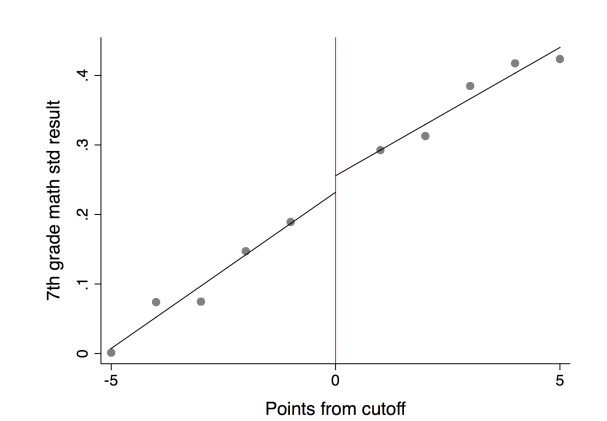
Notes: The figures plot the mean values of school characteristics for each placement score bin. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. All school cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 6: Standardized Test Results in 7th grade

(a) 7th grade Standardized Test (Spanish)



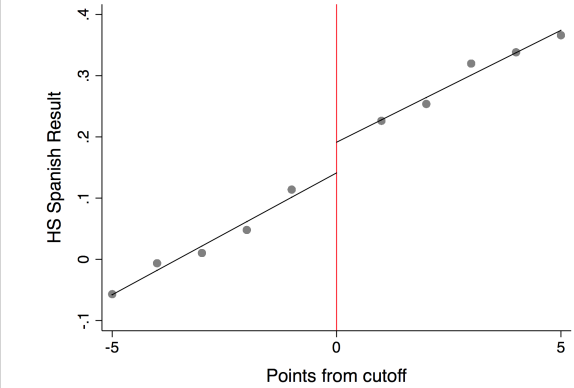
(b) 7th grade Standardized Test (Math)



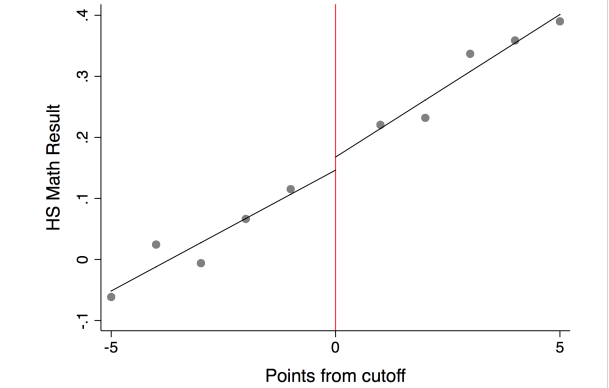
Notes: The figures plot the mean values of school standardized test scores for Math and Spanish in 7th grade (collected one year after assignment) for each placement score bin. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. All school cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 7: High School Exam Results

(a) HS Exam Result (Spanish)



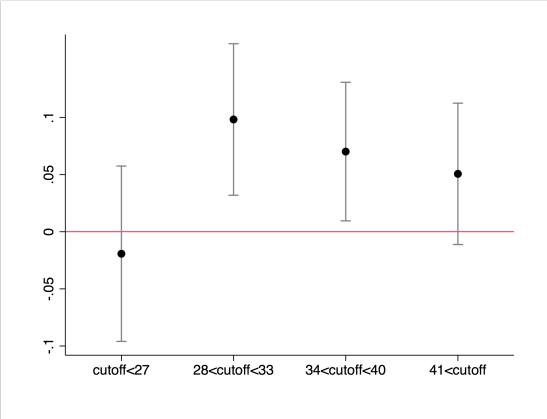
(b) HS Exam Result (Math)



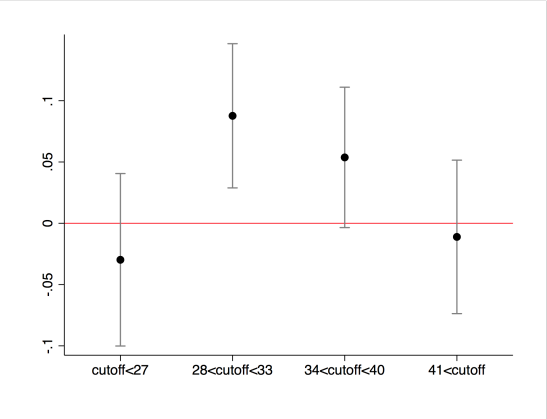
Notes: The figures plot the mean values of school standardized test scores for (a) the Spanish and (b) math section for the high school placement exam for each placement score bin. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. All cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 8: Heterogeneity in Spanish Results by School Cut-off

(a) 7th Grade Standardized Test (Spanish)



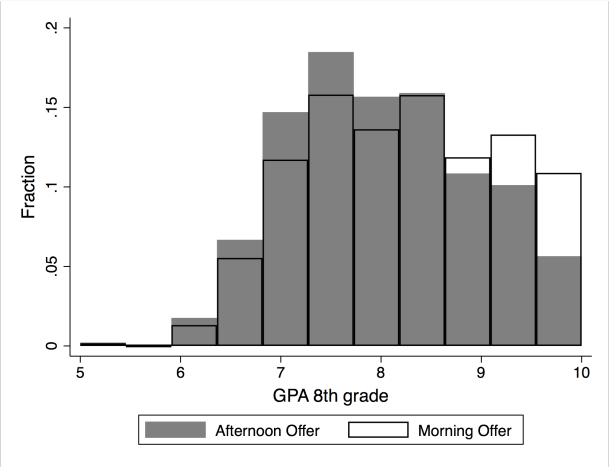
(b) HS Exam Result (Spanish)



Notes: The above figures plot coefficients for different ranges of entrance score cut-offs. The gray line are associated 95% confidence intervals.

Figure 9: GPA and School Offer

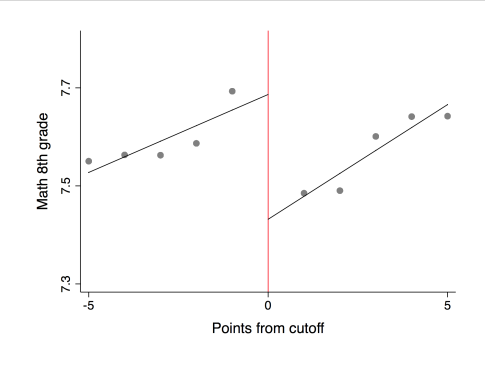
(a) 8th Grade GPA Histograms



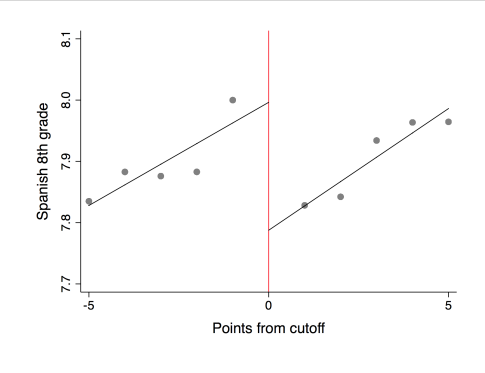
Notes: The figure shows 8th grade GPA histograms for the analytic sample by type of school offer.

Figure 10: School-based Assesment

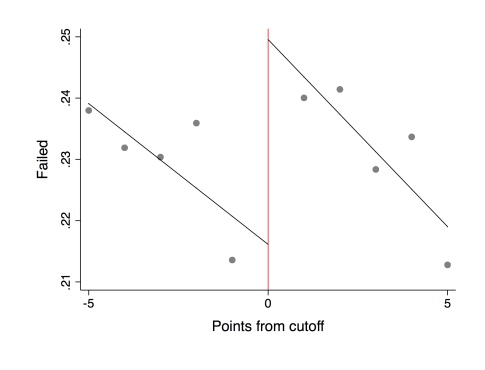
(a) 8th grade Math GPA



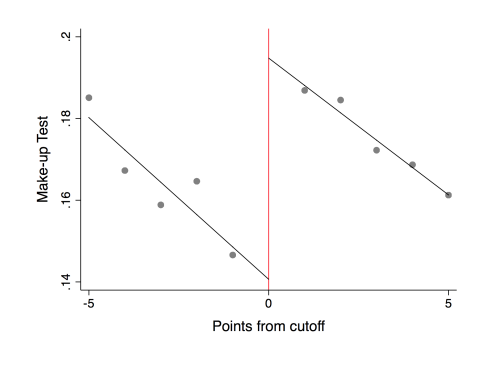
(b) 8th grade Spanish GPA



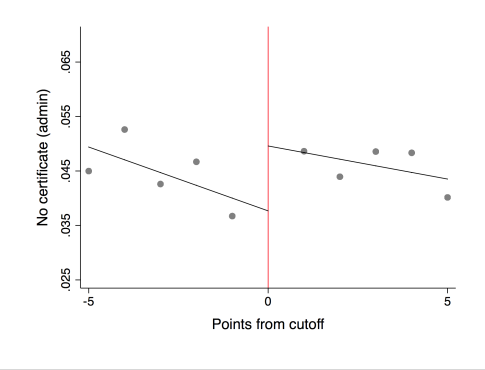
(c) Failed a class



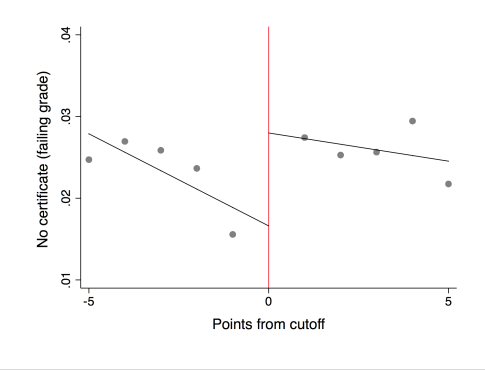
(d) Make-up Test



(e) No certificate (Admin Records)



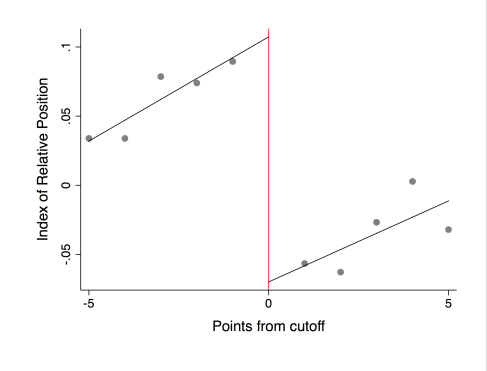
(f) No certificate (Failing Grade)



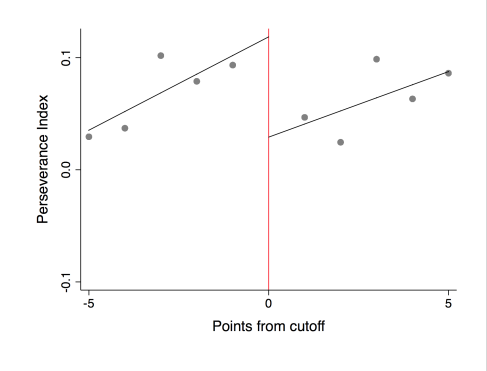
Notes: The figures plot the mean values of different measures of achievement and grade progression awarded at the school level for each placement score bin. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. All cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 11: Perceptions and Socioemotional Traits

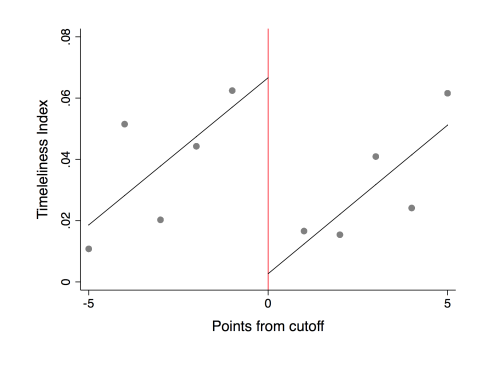
(a) Relative Position Index



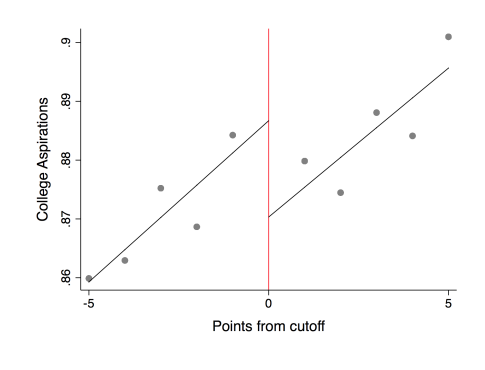
(b) Perseverance Index



(c) Time Management Index

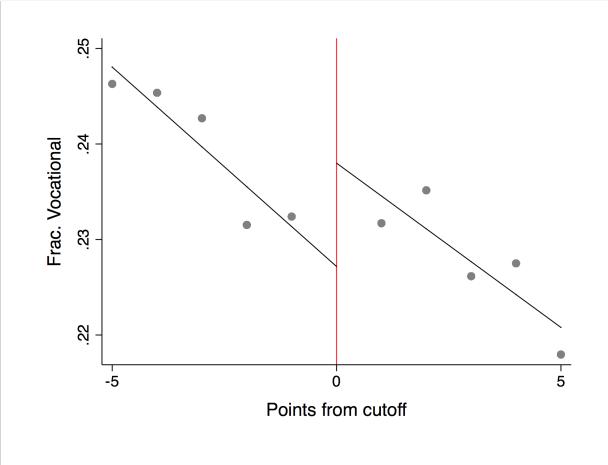


(d) Aspires to college or more



Notes: The figures plot the mean values of different measures of students perceptions for each placement score bin. The graphs show discontinuities for: (a) a relative position index, (b) a perseverance index, (c) time management index and (d) an indicator variable of aspiration to attend college or a postgraduate degree. For details on the questions used to construct these indexes, see footnotes in Table 1. All cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure 12: Fraction of Vocational High Schools



Notes: The figure plots the mean value of the fraction of vocational or technical high schools selected in students' portfolios for each placement score bin. All cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

10 Tables

Table 1: Summary Statistics

	Full Sample			Analytic Sample			RDD		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Female	0.49	0.50	285,739	0.51	0.50	82,566	0.51	0.50	32,181
Age	12.30	0.52	285,685	12.24	0.44	82,566	12.24	0.44	32,181
Mother middle school	0.41	0.49	284,743	0.49	0.50	82,566	0.49	0.50	32,181
Father middle school	0.35	0.48	284,988	0.42	0.49	82,565	0.42	0.49	32,181
Siblings	0.07	0.26	285,739	0.06	0.23	82,566	0.06	0.23	32,181
Close to school	0.37	0.48	285,739	0.33	0.47	82,566	0.33	0.47	32,181
Disability	0.01	0.12	285,739	0.01	0.08	82,566	0.01	0.07	32,181
Primary school in Mexico City	0.89	0.31	285,739	1.00	0.00	82,566	1.00	0.00	32,181
Private primary school	0.06	0.24	285,739	0.09	0.29	82,566	0.09	0.29	32,181
Placement score	31.79	9.46	279,683	35.36	9.49	82,566	35.46	8.07	32,181
Prefers morning shift	0.95	0.22	285,739	1.00	0.00	82,566	1.00	0.00	32,181
Total 5th grade score	0.00	1.00	230,294	0.26	0.98	82,566	0.27	0.94	32,181
Total 6th grade score	0.00	1.00	235,908	0.27	0.98	82,566	0.28	0.94	32,181
Spanish 7th grade score	-0.00	1.00	249,582	0.23	0.99	82,566	0.24	0.98	32,181
Math 7th grade score	0.00	1.00	249,582	0.22	0.99	82,566	0.23	0.97	32,181
Math 8th GPA	7.54	1.48	192,128	7.65	1.40	82,566	7.58	1.37	32,181
Spanish 8th GPA	7.81	1.48	191,916	7.94	1.39	82,566	7.90	1.38	32,181
Failed	0.24	0.43	191,157	0.22	0.41	82,566	0.23	0.42	32,181
No certificate	0.06	0.23	202,058	0.05	0.21	82,566	0.05	0.21	32,181
HS exam score	0.00	1.00	198,398	0.17	1.00	81,468	0.19	0.97	31,785
Aspire college	0.82	0.38	201,754	0.87	0.33	82,566	0.88	0.33	32,181
Aspire technical degree	0.13	0.33	201,754	0.11	0.31	82,566	0.11	0.31	32,181
Frac. vocational track HS	0.26	0.25	201,754	0.24	0.24	82,566	0.23	0.24	32,181
Frac. elite HS	0.56	0.28	201,754	0.58	0.28	82,566	0.59	0.27	32,181
Perseverance Index (2011 only)	0.03	0.73	85,431	0.08	0.73	35,525	0.07	0.73	13,496
Time Management Index (2012 only)	0.00	0.83	102,125	0.04	0.82	44,695	0.03	0.82	17,795
Relative Index (2011 only)	0.01	0.72	85,167	0.04	0.72	35,426	0.01	0.72	13,459

Notes: This table describes individual-level data. The full sample contains information for all students who applied for placement in a public middle school in Mexico City in 2011 and 2012. The analytic sample include observations as defined in Section 3 . The RDD sample restricts the analytic sample within 5 points of the discontinuity. Mother middle school and Father middle school are dichotomous variables taking value of one if the student's mother or father completed any education beyond middle school. Disability is a dichotomous variable if the student reports any disability in their middle school application form. Results for standardized tests in 5th, 6th, 7th grade and for the high school (HS) exam are standardized to have mean 0 and s.d. of 1. Frac. vocational track is the fraction of vocational schools listed by students in their HS application form (the rest would be academic) and Frac. elite HS to the fraction of elite high schools in students' high school portfolios. The perseverance index is constructed from questions that ask students how much the following statements describe them: *"Setbacks discourage me"*, *"I'm a diligent person"*, *"I finish everything that I start"*, *"I'm a hard worker"*. The relative index is a score from 1 (better than them) - 3 (worse than them) that asks students how well they think they perform relative to their peers in Math, Spanish, Biology and History. The time management index asks students the frequency with which: *"they establish priorities"*, *"they establish deadlines"*, *"they finish what they start"*, *"they plan their tasks"*. Indices are normalized by taking the average and dividing by the standard deviation of students who placed in the afternoon shift.

Table 2: Differential Attrition by Dataset

	(1) 5th grade	(2) 6th grade	(3) 7th grade	(4) 8th grade	(5) HS sample (1 yr)	(6) HS sample (2 yrs)
$1\{score \geq cutoff\}$	-0.001	-0.003	-0.004	0.026**	0.029***	0.006
	(0.005)	(0.005)	(0.006)	(0.011)	(0.009)	(0.008)
Observations	50873	50873	50873	22991	50873	50873
Controls	No	No	No	No	No	No
Mean LHS	0.09	0.07	0.08	0.13	0.25	0.22

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a more competitive school on indicators of attrition for each data set. All columns show results restricted to within 5 points of the cut-off placement score. The first, second, third and fourth columns show attrition from the standardized test (ENLACE) in 5th, 6th, 7th and 8th grade respectively. The dependent variable is a dummy that takes a value of one, if the student does not appear in the sample in the corresponding grade. There are no results for 8th grade for the 2012 cohort since universal standardized testing stopped in 2013. The fifth column shows attrition results from registration for the high school exam. The sixth column allows for registration within two years of their expected middle school graduation year. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for cut-off fixed effects.

Table 3: Baseline Characteristics

	Full Sample		**2011**		**2012**	
	$\hat{\beta}$	LHS Mean	$\hat{\beta}$	LHS Mean	$\hat{\beta}$	LHS Mean
	(1)	(2)	(3)	(4)	(5)	(6)
Test 5th	0.021	0.07	-0.009	0.10	0.044	0.04
	(0.023)		(0.034)		(0.029)	
Test 6th	0.008	0.07	-0.025	0.10	0.032	0.05
	(0.021)		(0.033)		(0.028)	
Female	0.010	0.51	0.022	0.52	0.000	0.51
	(0.014)		(0.021)		(0.018)	
Age	-0.000	12.25	0.013	12.25	-0.011	12.24
	(0.012)		(0.019)		(0.016)	
Mother Edu	0.006	0.44	0.000	0.44	0.012	0.43
	(0.013)		(0.019)		(0.017)	
Father Edu	0.007	0.38	0.002	0.38	0.011	0.38
	(0.013)		(0.019)		(0.018)	
Lives Near	-0.004	0.34	-0.003	0.34	-0.006	0.33
	(0.011)		(0.017)		(0.015)	
Sibling	-0.001	0.06	-0.004	0.07	0.001	0.05
	(0.006)		(0.011)		(0.008)	
Mother HH	-0.014	0.14	-0.019	0.18	-0.009	0.12
	(0.010)		(0.016)		(0.011)	
Mother works	-0.007	0.44	-0.007	0.51	-0.008	0.39
	(0.013)		(0.021)		(0.016)	
Family size	0.038	4.66	0.002	4.68	0.066	4.65
	(0.040)		(0.060)		(0.053)	
Disability	-0.002	0.01	-0.004	0.01	-0.000	0.01
	(0.002)		(0.003)		(0.003)	
BMI	-0.061	20.51	-0.147	20.57	0.009	20.47
	(0.096)		(0.145)		(0.131)	
Mor. shift prim.	0.008	0.81	0.022	0.82	-0.003	0.80
	(0.010)		(0.015)		(0.013)	
	F-stat: 0.49		F-stat: 0.70		F-stat: 0.43	

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows estimates of the effect of an offer to a more competitive school on pre-assignment characteristics. Results are restricted to a 5 point window from the cut-off placement score. Test 5th and Test 6th refer to the results from standardized test scores if 5th and 6th grades, respectively. Lives close by is a dummy variable on whether student lives close to school, Mother Edu and Father Edu are dummy variables for mother and father having completed more than middle school respectively, sibling denotes whether the student has a sibling in the school, Mother HH is a dummy variable if the student only lives with the mother, Mother works is a dummy variable if the mother works outside the home, Family size is the number of adults living with the student, Disability is a dummy variable that indicates whether student reported any disability, BMI is a measure of student's body mass index constructed by dividing their weight in kilograms by the square of their height in meters, and Mor. shift prim. is a dummy variable indicating whether student attended a morning shift in primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended primary school level. All regressions control for cut-off fixed effects.

Table 4: Compliance with School Assignment

	(1) Complied	(2) First choice morning shift	(3) Any morning shift
$1\{score \geq cutoff\}$	0.205***	0.803***	0.680***
	(0.028)	(0.014)	(0.019)
Observations	32181	32181	32181
Mean LHS	0.67	0.09	0.30

Notes: ***p<0.01, **p<0.05, *p<0.10. Results are restricted to a 5 point window from the cut-off placement score. Complied is an indicator variable that takes a value of one if the student reports being in the school he or she was assigned to. First choice morning shift indicates whether student attends their first choice facility in their morning shift. Any morning shift indicates whether the student matriculates in any school in the morning shift. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 5: School Characteristics

	(1) Peers' scores	(2) Incentive program	(3) Teacher masters	(4) Principal masters	(5) Teacher-student ratio	(6) Log(Cost)
$1\{score \geq cutoff\}$	0.625***	0.074***	-0.002	0.079***	-0.008***	-0.031
	(0.020)	(0.007)	(0.002)	(0.015)	(0.001)	(0.029)
Observations	32181	32181	32181	32181	32181	20964
Mean LHS	0.14	0.22	0.02	0.17	0.04	7.62

Notes: ***p<0.01, **p<0.05, *p<0.10. Results are restricted to a 5 point window from the cut-off placement score. Peers' scores refers to the standardized mean score of the placement exam of the school-cohort that the student attends. Incentive program is the fraction of teachers that participate in carrera magisterial program in the school students attend. Teacher masters and Principal masters is the fraction of teachers and principals with masters degrees or more education respectively. Log(Cost) is the logarithm of reported school costs (not all schools reported). Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 6: Effects on Standarized Tests in 7th Grade

	(1) Spanish	(2) Spanish	(3) Math	(4) Math
$1\{score \geq cutoff\}$	0.063***	0.060***	0.015	0.016
	(0.023)	(0.020)	(0.025)	(0.021)
Observations	32181	32181	32181	32181
Controls	No	Yes	No	Yes
Mean LHS	0.11	0.11	0.10	0.10

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to morning shift school on standardized test scores in 7th grade. The results are restricted to 5 points from cut-off placement score. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 7: Effects on High School Exam

	(1) HS Exam Spanish	(2) HS Exam Spanish	(3) HS Exam Math	(4) HS Exam Math
$1\{score \geq cutoff\}$	0.037*	0.036*	0.003	0.004
	(0.022)	(0.019)	(0.021)	(0.018)
Observations	31785	31785	31785	31785
Controls	No	Yes	No	Yes
Mean LHS	0.02	0.02	0.03	0.03

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on results for the Spanish and math sections of the high school entrance exam (the number of observations reflects the fact that some students do not take the exam). Column (1) and (2) restricts to scores in the verbal ability and Spanish sections of the exam. Column (3) and (4) restricts to the scores in the math and mathematical ability sections. The results are restricted to within 5 points of the cut-off placement score. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 8: Heterogeneity in Learning Effects

	(1) 7th grade Spanish	(2) 7th grade math	(3) HS Exam Spanish	(4) HS Exam math
Panel A. Gender				
$1\{score \geq cutoff\}$	0.054*	0.016	-0.005	-0.001
	(0.028)	(0.028)	(0.027)	(0.027)
$1\{score \geq cutoff\} * female$	-0.005	-0.016	0.059	-0.010
	(0.038)	(0.034)	(0.037)	(0.036)
Observations	32181	32181	31785	31785
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.11	0.10	0.02	0.03
Panel B. 6th grade standardized results				
$1\{score \geq cutoff\}$	0.050*	0.009	0.011	-0.042*
	(0.027)	(0.029)	(0.026)	(0.025)
$1\{score \geq cutoff\} * below\ median\ scores$	0.032	0.026	0.061	0.127***
	(0.039)	(0.040)	(0.039)	(0.039)
Observations	32181	32181	31785	31785
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.11	0.10	0.02	0.03
Panel C. Mother's education				
$1\{score \geq cutoff\}$	0.021	-0.026	0.002	-0.044*
	(0.025)	(0.027)	(0.025)	(0.025)
$1\{score \geq cutoff\} * mom\ middle\ school\ or\ less$	0.055	0.057	0.047	0.084**
	(0.036)	(0.038)	(0.037)	(0.036)
Observations	32181	32181	31785	31785
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.11	0.10	0.02	0.03

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows heterogeneous effects by gender, whether the student scored below the median in the 6th grade standardized exam, and by whether his or her mother completed middle school or less. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 9: School-Based Assessments

Panel A. Grades						
	GPA 8th grade		GPA 8th Math		GPA 8th Spanish	
	(1)	(2)	(3)	(4)	(5)	(6)
$1\{score \geq cutoff\}$	-0.200***	-0.206***	-0.264***	-0.268***	-0.228***	-0.235***
	(0.030)	(0.029)	(0.038)	(0.037)	(0.036)	(0.035)
Observations	32181	32181	32181	32181	32181	32181
Controls	No	Yes	No	Yes	No	Yes
Mean LHS	7.99	7.99	7.59	7.59	7.90	7.90
Panel B. Academic Progress						
	Failed Class		No Certificate		Failed to Complete	
	(7)	(8)	(9)	(10)	(11)	(12)
$1\{score \geq cutoff\}$	0.039***	0.041***	0.014***	0.014***	0.013***	0.013***
	(0.011)	(0.010)	(0.005)	(0.005)	(0.004)	(0.004)
Observations	32181	32181	32181	32181	32181	32181
Controls	No	Yes	No	Yes	No	Yes
Mean LHS	0.23	0.23	0.04	0.04	0.02	0.02

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on school assessments. All columns show results for a bandwidth of 5 points within the cut-off. The dependent variables are: the overall 8th grade GPA, the average score in Math in 8th grade, the average score in Spanish in 8th grade, a dummy for whether student reports failing at least one class during previous year, a dummy for not having the middle school certificate (within two years of predicted graduation date) and a dummy for having at least one failed class in 8th grade by 2017. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 10: Heterogeneity in Grade Progression and Completion

	(1) 8th Grade GPA	(2) Failed	(3) No Certificate	(4) Failed to Complete
Panel A. Gender				
$1\{score \geq cutoff\}$	-0.265***	0.048***	0.024***	0.020***
	(0.042)	(0.016)	(0.009)	(0.007)
$1\{score \geq cutoff\} * female$	0.104*	-0.012	-0.017*	-0.012
	(0.056)	(0.020)	(0.010)	(0.008)
Observations	32181	32181	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	7.99	0.23	0.04	0.02
Panel B. 6th grade standardized results				
$1\{score \geq cutoff\}$	-0.209***	0.036***	0.011*	0.008**
	(0.036)	(0.013)	(0.006)	(0.004)
$1\{score \geq cutoff\} * below\ median\ scores$	0.025	0.011	0.010	0.011
	(0.061)	(0.024)	(0.011)	(0.008)
Observations	32181	32181	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	7.99	0.23	0.04	0.02
Panel C. Mother's education				
$1\{score \geq cutoff\}$	-0.171***	0.033**	0.012*	0.012**
	(0.038)	(0.013)	(0.006)	(0.005)
$1\{score \geq cutoff\} * mom\ middle\ school\ or\ less$	-0.087	0.019	0.007	0.003
	(0.057)	(0.021)	(0.010)	(0.007)
Observations	32181	32181	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	7.99	0.23	0.04	0.02

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows heterogeneous effects by gender, whether the student scored below the median in the 6th grade standardized exam, and by whether his or her mother completed middle school or less. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 11: Students' Perceptions, Non-cognitive Skills and Aspirations

	Relative Index		Perseverance Index		Time Management Index		Aspires College		Aspires Tech. Degree	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$1\{score \geq cutoff\}$	-0.180***	-0.181***	-0.098***	-0.101***	-0.068**	-0.072***	-0.017**	-0.019**	0.017**	0.018**
	(0.027)	(0.027)	(0.030)	(0.029)	(0.028)	(0.028)	(0.008)	(0.008)	(0.008)	(0.007)
Observations	13459	13459	13496	13496	17795	17795	32181	32181	32181	32181
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean LHS	0.06	0.06	0.07	0.07	0.04	0.04	0.87	0.87	0.11	0.11
Lower Bound	-0.219***	-0.218***	-0.064**	-0.066**	-0.023	-0.027				
	(0.027)	(0.026)	(0.029)	(0.028)	(0.028)	(0.028)				
Upper Bound	-0.129***	-0.132***	-0.142***	-0.144***	-0.125***	-0.128***				
	(0.025)	(0.025)	(0.029)	(0.028)	(0.028)	(0.028)				

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on different measures of students' self-perceptions, non-cognitive skills and aspirations. All columns show results for a bandwidth of 5 points within the cut-off. See Table 1 for a description of the indices. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 12: High School Portfolio Choices

	Share Vocational	Share Vocational
	(1)	(2)
$1\{score \geq cutoff\}$	0.011*	0.012**
	(0.006)	(0.006)
Observations	32181	32181
Controls	No	Yes
Mean LHS	0.24	0.24

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on the share of vocational programs students' applied for. Avg. Score column refers to the average of previous year high school exam cut-offs for all programs that student listed. Share vocational refer to the fraction of vocational or technical programs that student listed. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 13: Heterogeneity in Non-Cognitive, Aspirations and Track Choices

	(1) Perseverance Index	(2) Time Management	(3) Aspire College	(4) Frac. Vocational Choices
Panel A. Gender				
$1\{score \geq cutoff\}$	-0.088**	-0.040	-0.014	0.014*
	(0.038)	(0.043)	(0.012)	(0.008)
$1\{score \geq cutoff\} * female$	-0.038	-0.054	-0.009	-0.004
	(0.053)	(0.058)	(0.016)	(0.011)
Observations	13496	17795	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.07	0.04	0.87	0.24
Panel B. 6th grade standardized results				
$1\{score \geq cutoff\}$	-0.142***	-0.073*	-0.020**	0.008
	(0.036)	(0.037)	(0.009)	(0.007)
$1\{score \geq cutoff\}$*below median scores*	0.131**	0.002	0.009	0.009
	(0.061)	(0.058)	(0.017)	(0.012)
Observations	13496	17795	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.07	0.04	0.87	0.24
Panel C. Mother's education				
$1\{score \geq cutoff\}$	-0.182***	-0.054	-0.003	0.012
	(0.039)	(0.036)	(0.008)	(0.007)
$1\{score \geq cutoff\}$*mom middle school or less*	0.163***	-0.025	-0.035**	0.003
	(0.056)	(0.053)	(0.016)	(0.012)
Observations	13496	17795	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.07	0.04	0.87	0.24

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows heterogeneous effects by gender, whether the student scored below the median in the 6th grade standardized exam, and by whether his or her mother completed middle school or less. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

Table 14: Changes in Student and Parent Behavior

Panel A. Student Behavior

	Never Skipped School	Never Skipped Class	Never practiced multiple choice	Works
	(1)	(2)	(3)	(4)
$1\{score \geq cutoff\}$	0.014	0.011*	-0.004	-0.003
	(0.013)	(0.006)	(0.010)	(0.011)
Observations	32181	32181	14155	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.43	0.92	0.09	0.26

Panel B. Parent Behavior

	Adult Monitors Index	Private Prep Course
	(5)	(6)
$1\{score \geq cutoff\}$	0.002	0.011
	(0.031)	(0.012)
Observations	13709	32181
Controls	Yes	Yes
Mean LHS	0.02	0.56
Lower Bound	-0.038***	
	(0.014)	
Upper Bound	0.019	
	(0.035)	

Panel C. Peer Behavior

	Never been hit	Never been insulted	Never been mocked
	(7)	(8)	(9)
$1\{score \geq cutoff\}$	-0.002	0.007	-0.002
	(0.007)	(0.011)	(0.010)
Observations	32181	32181	32181
Controls	Yes	Yes	Yes
Mean LHS	0.92	0.71	0.82

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on students, parents and peers' behavior. All columns show results for a bandwidth of 5 points within the cut-off. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level. All regressions control for cut-off fixed effects.

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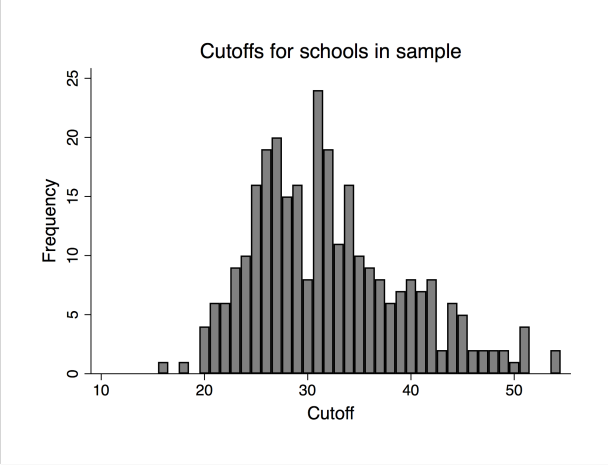
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A Additional Figures and Tables

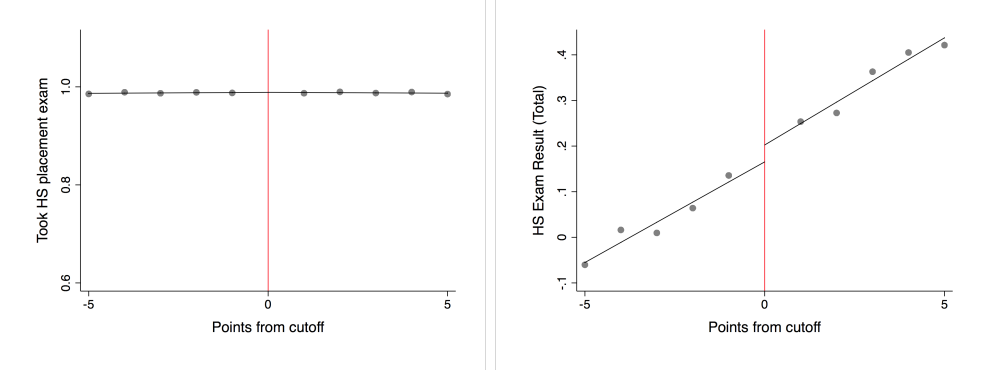
Figure A1: School Cut-offs



Notes: This figure shows the distribution of grades at which the within facility cut-offs take place for all schools in the sample.

Figure A2: Additional High School Exam Results

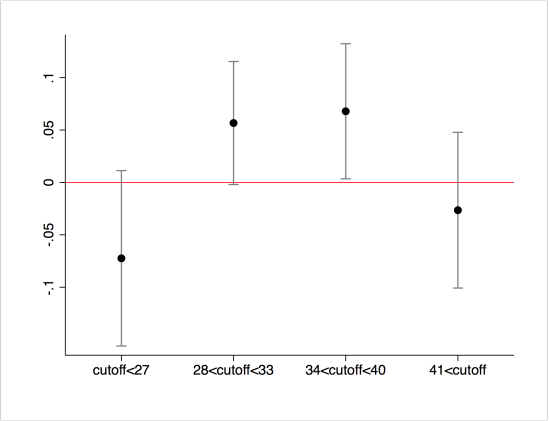
(a) Took High School Exam (b) High School Exam Result (All Subjects)



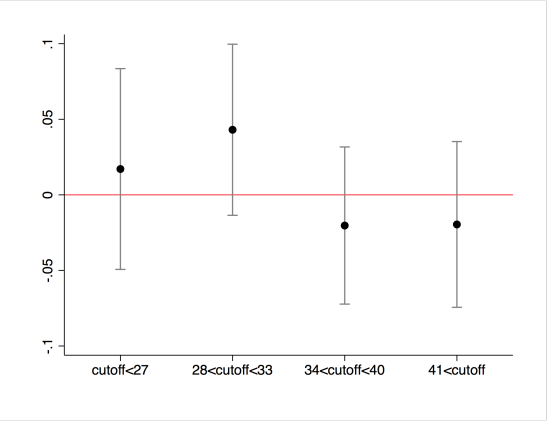
Notes: The above figures show discontinuities for: (a) taking the high school placement exam (COMIPEMS), (b) total standardized scores in all subjects. The solid lines are fitted values of the regression of the dependent variable on a linear trend on the placement score, estimated separately for each side of the cut-off. Cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure A3: Heterogeneity in Math Results by School Cut-off

(a) 7th Grade Standardized Test (Math)



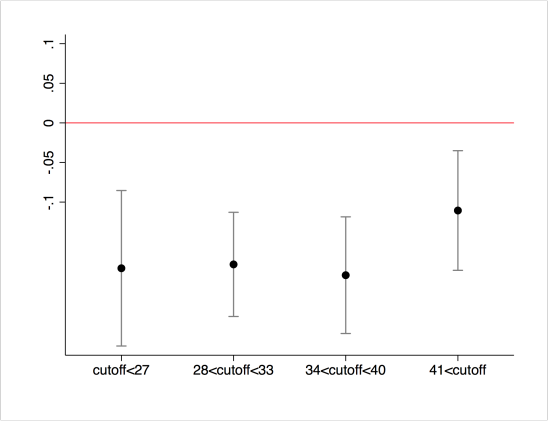
(b) HS Exam Result (Math)



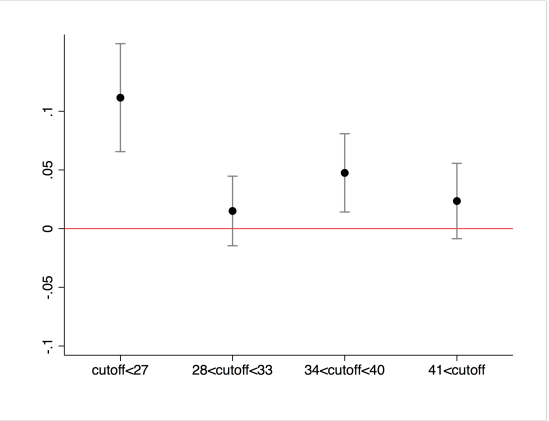
Notes: The above figures show heterogeneous treatment effects by school admission cut-off for the math section of standardized tests. The gray lines show 95% confidence intervals. Cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure A4: Heterogeneity in School-Based Assesments by School Cut-off

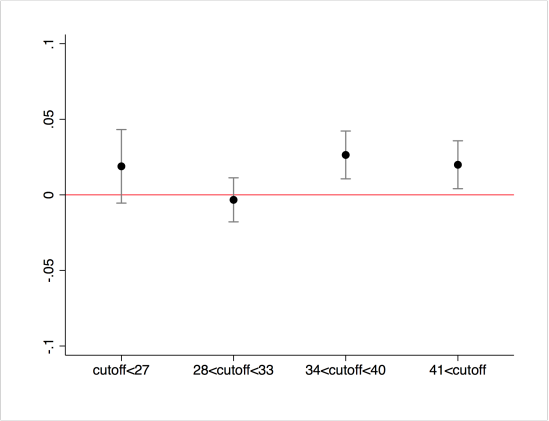
(a) GPA



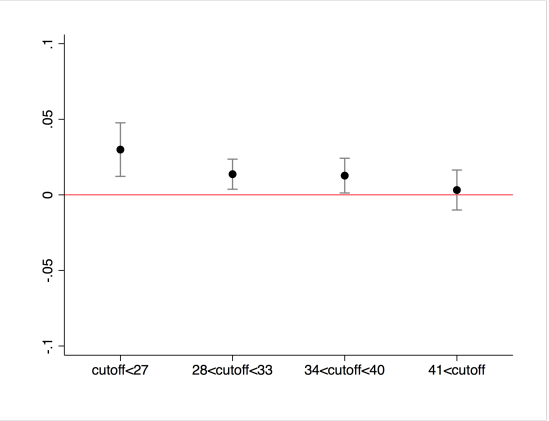
(b) Failed Class



(c) No Certificate



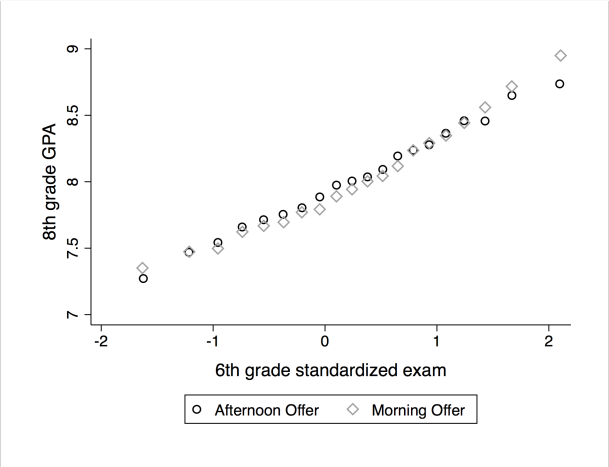
(d) Failed to Complete



Notes: The above figures show heterogeneous treatment effects by school admission cut-off for school-based assessments. The gray lines show 95% confidence intervals. Cut-offs are normalized to zero. Results are based on the 2011 and 2012 applicant cohorts, and restricted to those within 5 points of within-facility cut-offs.

Figure A5: GPA and School Offer

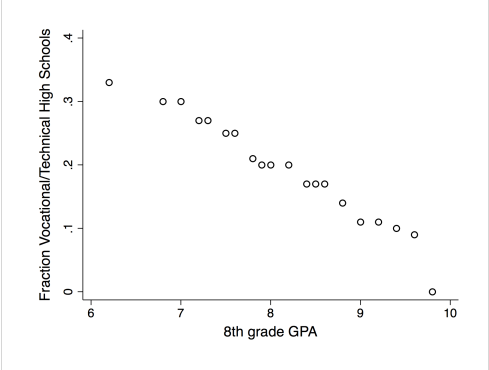
(a) 6th grade standardized test and 8th grade GPA



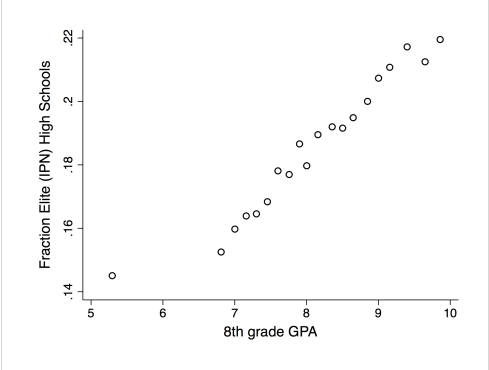
Notes: The figure shows a binscatter plot of self-reported GPA in 8th grade and standardized results from the 6th grade standardized test by whether the student received a morning or an afternoon offer.

Figure A6: GPA and Vocational/Technical Track Choices

(a) GPA and Voc./Tech. High School Track



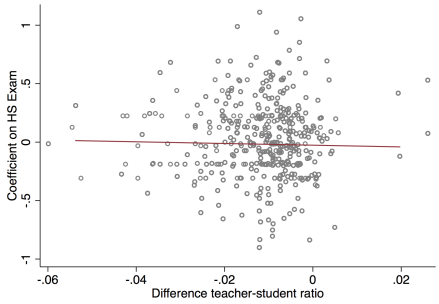
(b) GPA and Elite Tech. Track



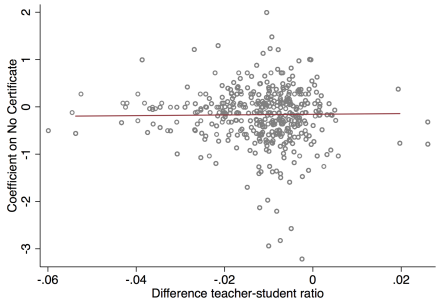
Notes: The figure shows a binscatter plot of self-reported GPA in 8th grade and the fraction of (a) technical or vocational schools that students select (excluding elite schools) and the fraction of (b) elite technical schools that students select.

Figure A7: Correlations of Effects and Differences in Teacher-Student Ratio

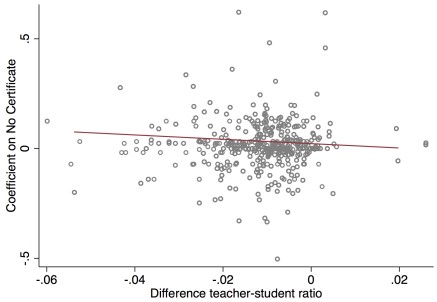
(a) Spanish High School Exam



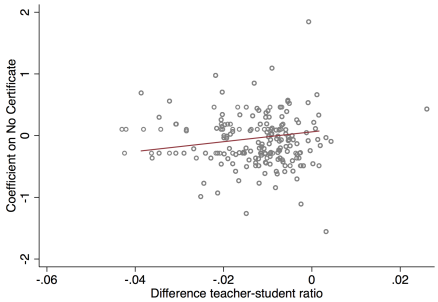
(b) GPA 8th Grade



(c) No Certificate



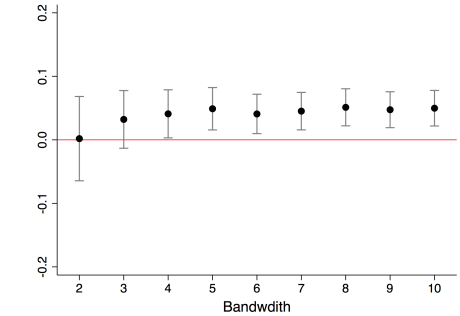
(d) Perseverance Index



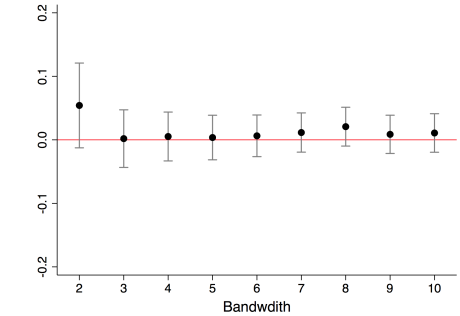
Notes: The figure shows scatterplots of the difference in teacher-student ratios between morning and afternoon schools for a given facility and the coefficients of selected variables estimated for each facility.

Figure A8: Bandwidth Selection for 7th grade tests

(a) 7th grade Spanish standardized test



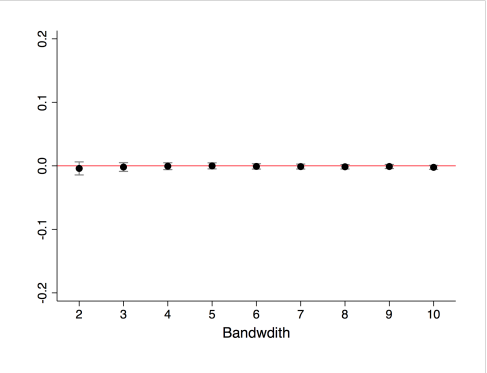
(b) 7th grade math standardized test



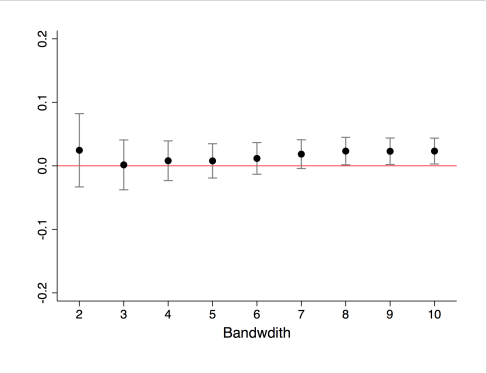
Notes: The graphs show the estimated coefficients of an offer to a better school for different bandwidths. The gray lines show 90% confidence intervals.

Figure A9: Bandwidth Selection for High School Exam

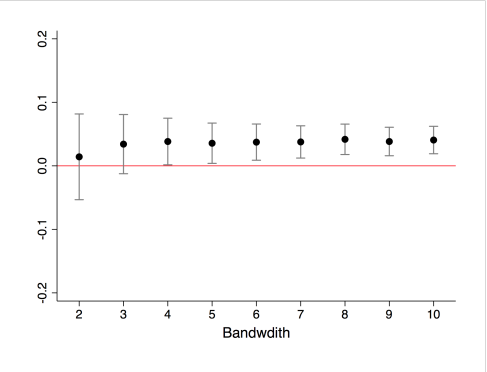
(a) Took High School Exam (All)



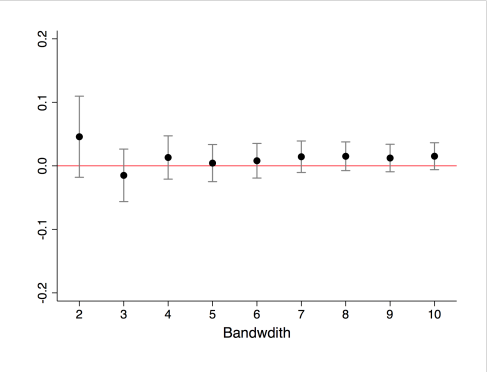
(b) Results on High School Exam (All)



(c) Results on High School Exam (Spanish)



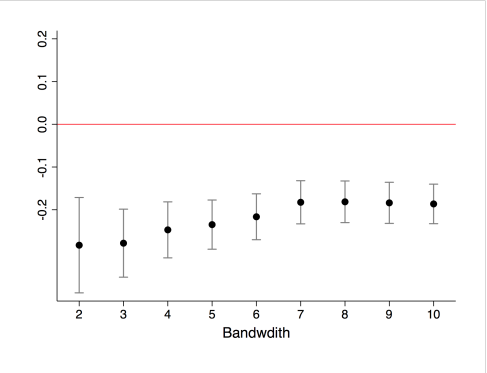
(d) Results on High School Exam (Math)



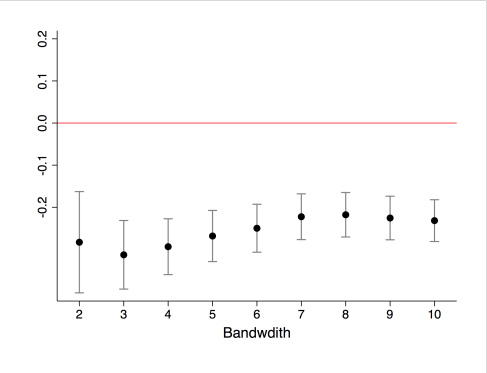
Notes: The graphs show the estimated coefficients of an offer to a better school for different bandwidths. The gray lines show 90% confidence intervals.

Figure A10: School-Based Assesment Bandwidth

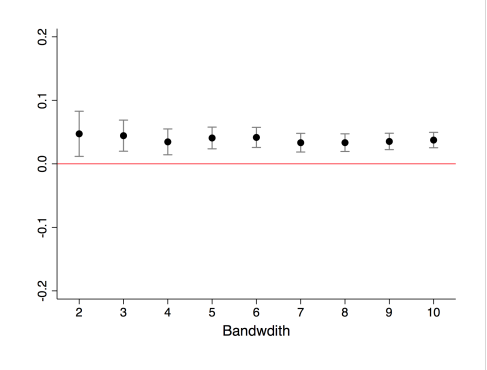
(a) 8th grade Spanish GPA



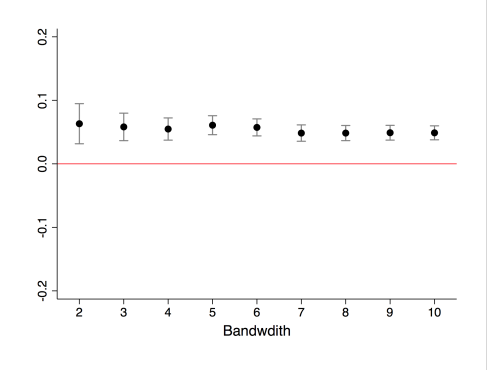
(b) 8th grade Math GPA



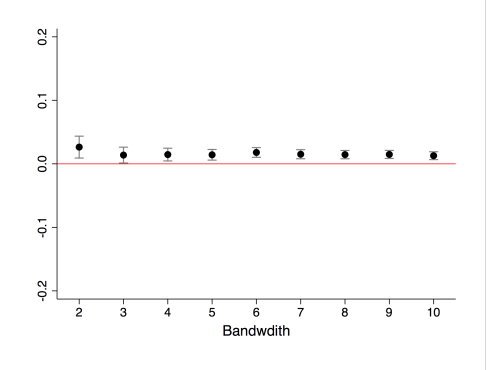
(c) Failed a class



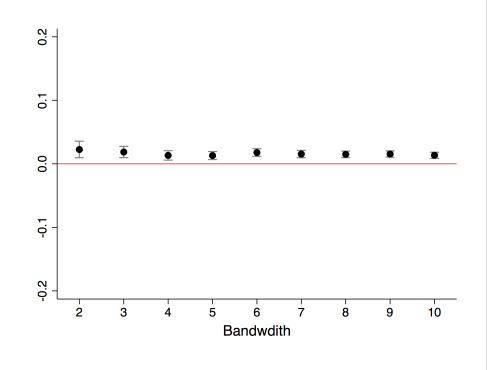
(d) Make-up Test



(e) No certificate (Admin Records)



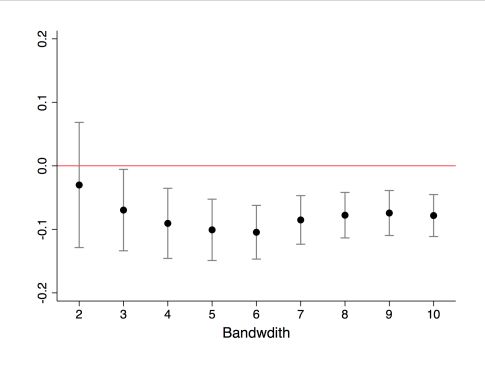
(f) No certificate (Failing Grade)



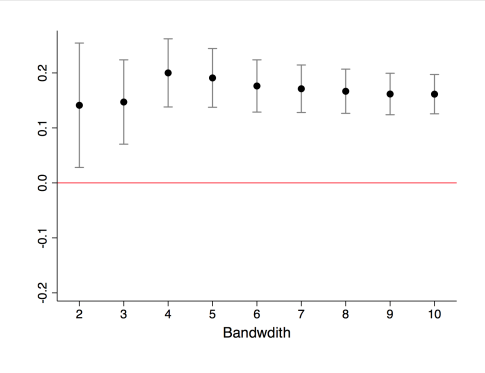
Notes: The graphs show the estimated coefficients of an offer to a better school for different bandwidths. The gray lines show 90% confidence intervals.

Figure A11: Bandwidth Selection for Socioemotional and Aspirations Measures

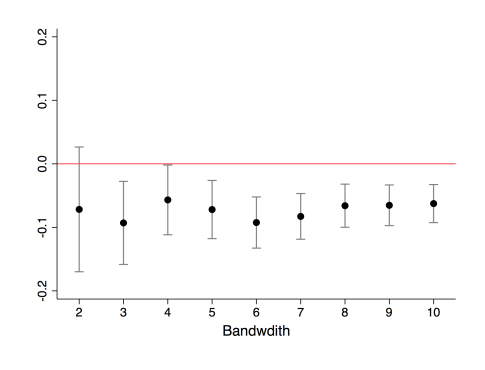
(a) Perseverance Index



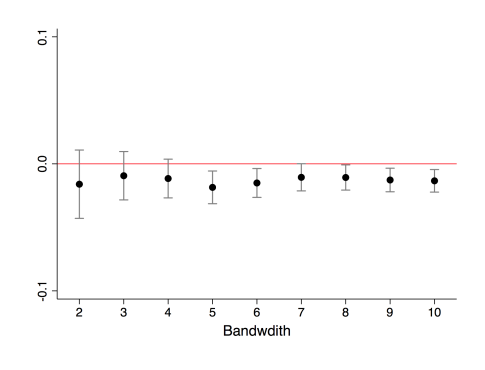
(b) Relative Performance Index



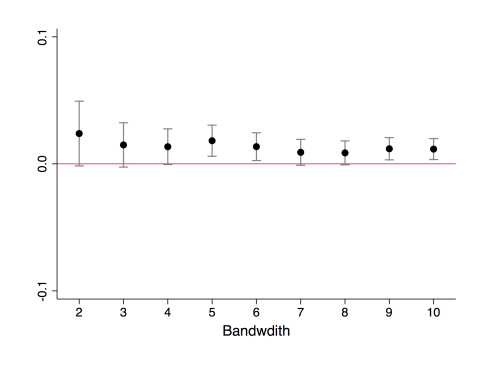
(c) Time Management Index



(d) Aspirations for College or More

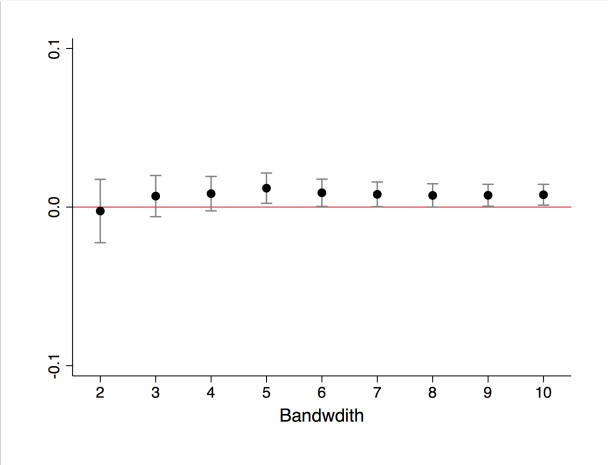


(e) Aspirations for Technical Degree



Notes: The graphs show the estimated coefficients of an offer to a better school for different bandwidths. The gray lines show 90% confidence intervals.

Figure A12: Bandwidth Selection for Fraction of Vocational High Schools



Notes: The graphs show the estimated coefficients of an offer to a better school for different bandwidths. The gray lines show 90% confidence intervals.

Table A1: Matching Rates Across Datasets

	Overall Matching %
ENLACE 5th grade	81%
ENLACE 6th grade	83%
ENLACE 7th grade	88%
ENLACE 8th grade (2011 cohort only)	82%
COMIPEMS	71%
PLANEA 9th grade (2012 cohort only)	13%

Notes: This table shows the percentage match rate for all applicants to middle schools in 2011 and 2012. ENLACE tests were meant to be applied to the universe of students. The PLANEA test was applied to a random sample of students in each school.

Table A2: Differential Attrition

	(1) 5th grade	(2) 6th grade	(3) 7th grade (1 yr)	(4) 7th grade (2 yrs)	(5) 8th grade (1 yr)	(6) HS sample (1 yr)	(7) HS sample (2 yrs)
Panel A. Attrition 2011 Cohort (within facility cut-offs)							
$1\{score \geq cutoff\}$	-0.002	-0.002	-0.003	-0.003	0.026**	0.030**	0.007
	(0.006)	(0.004)	(0.008)	(0.007)	(0.011)	(0.013)	(0.012)
Observations	22991	22991	22991	22991	22991	22991	22991
Controls	No	No	No	No	No	No	No
Mean LHS	0.05	0.02	0.08	0.07	0.13	0.22	0.20
Panel B. Attrition 2012 Cohort (within facility cut-offs)							
$1\{score \geq cutoff\}$	-0.000	-0.003	-0.004			0.028**	0.006
	(0.008)	(0.008)	(0.008)			(0.011)	(0.011)
Observations	27882	27882	27882			27882	27882
Controls	No	No	No			No	No
Mean LHS	0.12	0.10	0.09			0.27	0.24
Panel C. Attrition by shift cut-offs (pooled)							
$1\{score \geq cutoff\}$	-0.001	-0.003	-0.004	-0.001	0.026**	0.029***	0.006
	(0.005)	(0.005)	(0.006)	(0.003)	(0.011)	(0.009)	(0.008)
Observations	50873	50873	50873	50873	22991	50873	50873
Controls	No	No	No	No	No	No	No
Mean LHS	0.09	0.07	0.08	0.59	0.13	0.25	0.22
Panel D. Attrition by across facility cut-offs							
$1\{score \geq cutoff\}$	-0.001	-0.004	-0.028***	-0.010***	-0.012	0.010	0.011
	(0.007)	(0.005)	(0.006)	(0.003)	(0.012)	(0.011)	(0.010)
Observations	36885	36885	36885	36885	15687	36885	36885
Controls	No	No	No	No	No	No	No
Mean LHS	0.08	0.06	0.11	0.61	0.16	0.27	0.24

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a more selective school on measures of attrition for each dataset. All columns show results restricting to within 5 points of the cut-off placement score. The first, second, third, fourth and fifth columns show attrition from the standardized test (ENLACE) in 5th, 6th, 7th (allowing 1 year after), 7th (allowing 2 years after) and 8th grade respectively. The dependent variable is a dummy that takes a value of one, if the student does not appear in the sample in the corresponding grade. There are no results for 8th grade for the 2012 cohort since universal standardized testing stopped in 2013. The sixth column shows attrition results from registration for the high school exam. The seventh column allows for registration within two years of the expected middle school graduation year. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for cut-off fixed effects.

Table A3: Discontinuities in School Level Characteristics

	Average School:				
	Placement score (predicted)	6th grade test	SES index	Mother education	Father education
	(1)	(2)	(3)	(4)	(5)
$1\{score \geq cutoff\}$	1.008***	0.387***	0.159***	0.093***	0.087***
	(0.021)	(0.016)	(0.010)	(0.004)	(0.004)
Observations	32181	32181	32181	32181	32181
Mean LHS	0.03	0.12	-0.02	0.45	0.38

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a selective school on measures of student characteristics averaged at the school level. Peers' placement score (predicted) is the estimated peer mean average placement scores using the predicted (rather than experienced) allocation. Peers' 6th grade scores is the mean scores for the results of the low-stakes 6th grade standardize exam. The SES index is constructed taking the principal component of the following variables: (i) number of bathrooms in the household, (ii) whether they have a car, (iii) whether they have a microwave, (iv) whether they have a washing machine. Avg. Mother and Father education indicate the average proportion of mothers and fathers (respectively) that have completed any additional years of education beyond middle school. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for cut-off fixed effects.

Table A4: Effects on Standarized Tests in 8th Grade (2011 cohort only)

	Spanish	Spanish	Math	Math
	(1)	(2)	(3)	(4)
$1\{score \geq cutoff\}$	0.055	0.058	-0.053	-0.038
	(0.039)	(0.035)	(0.039)	(0.037)
Observations	13789	13789	13789	13789
Controls	No	Yes	No	Yes
Mean LHS	0.12	0.12	0.17	0.17
Upper Bound	0.111***	0.111***	0.028	0.028
	(0.028)	(0.027)	(0.030)	(0.025)
Lower Bound	0.015	0.015	-0.074***	-0.074**
	(0.026)	(0.030)	(0.029)	(0.032)

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a selective school on standardized test scores for 8th grade. The results are restricted to 5 points from the cut-off placement score. The upper bound and lower bound show bounded estimates using a trimming procedure as per Lee (2009). Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for cut-off fixed effects.

Table A5: Effects on High School Exam

	(1) HS Exam Taken	(2) HS Exam Taken	(3) HS Exam (All Subjects)	(4) HS Exam (All Subjects)
$1\{score \geq cutoff\}$	0.000	0.000	0.020	0.019
	(0.003)	(0.003)	(0.019)	(0.017)
Observations	32181	32181	31785	31785
Controls	No	Yes	No	Yes
Mean LHS	0.99	0.99	0.04	0.04

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on taking the high school entrance exam and the overall exam performance including all subjects. The results are restricted to 5 points from the cut-off placement score. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for cut-off fixed effects.

Table A6: Attrition from 9th Grade Standardized Exam

	9th grade attrition
	(1)
$1\{score \geq cutoff\}$	0.075***
	(0.016)
Observations	18026
Controls	No
Mean LHS	0.64

Notes: ***p<0.01, **p<0.05, *p<0.10. This table shows parametric estimates of the effect of an offer to a morning shift school on the probability of not appearing in an exam implemented in 9th grade with a random sample of students.The results are restricted to 5 points from the cut-off placement score.All regressions control for school cut-off fixed effects. Results are restricted to the 2012 cohort in column (1). Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for cut-off fixed effects.

Table A8: Correlates of First Year Attrition in High School Exam

	Assigned Morning	Assigned Afteroon
	(1)	(2)
Panel A. Pre-assignment Characteristics		
Female	-0.030***	-0.020***
	(0.004)	(0.004)
Age	0.002	0.000
	(0.004)	(0.005)
Disability	0.026	0.032
	(0.038)	(0.038)
Mother Edu	0.003	0.001
	(0.004)	(0.004)
Test 5th grade	-0.024***	-0.016***
	(0.003)	(0.003)
Panel B. Outcomes (2015 survey)		
HS exam score	-0.017***	-0.008***
	(0.003)	(0.003)
GPA 8th grade	-0.013***	-0.010***
	(0.002)	(0.002)
No certificate	0.020*	0.014
	(0.011)	(0.011)

Notes: ***p<0.01, **p<0.05, *p<0.10. This table reports the coefficients from OLS regressions for the 2011 cohort on an indicator of whether the student was delayed for a year in taking the HS placement exam (i.e. registered to take the exam in 2015 instead of 2014). The regression is limited to 5 points within each side of the cut-offs. The first panel reports characteristics from pre-assignment. The second panel reports outcomes reported in the 2015 survey. Heteroskedasticity-robust standard errors are in parenthesis.

Table A9: Heterogeneity in Student, Parent and Peer Behavior

	Never skip class	Not practice	Private prep course	Bully Index
	(1)	(2)	(3)	(4)
Panel A. Heterogeneity by gender				
$1\{score \geq cutoff\}$	-0.017	0.004	0.009	-0.002
	(0.011)	(0.015)	(0.018)	(0.027)
$1\{score \geq cutoff\} * female$	0.030**	-0.019	0.006	0.010
	(0.013)	(0.021)	(0.025)	(0.033)
Observations	32181	14155	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.92	0.09	0.56	0.10
Panel B. Heterogeneity by previous standardized scores				
$1\{score \geq cutoff\}$	-0.002	-0.005	0.011	0.005
	(0.008)	(0.012)	(0.015)	(0.023)
$1\{score \geq cutoff\}$*below median scores*	0.007	0.007	0.007	-0.008
	(0.015)	(0.023)	(0.025)	(0.038)
Observations	32181	14155	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.92	0.09	0.56	0.10
Panel C. Heterogeneity by mother's education				
$1\{score \geq cutoff\}$	-0.002	0.000	0.007	0.009
	(0.009)	(0.013)	(0.017)	(0.024)
$1\{score \geq cutoff\}$*mom middle school or less*	0.002	-0.008	0.009	-0.014
	(0.013)	(0.018)	(0.026)	(0.037)
Observations	32181	14155	32181	32181
Controls	Yes	Yes	Yes	Yes
Mean LHS	0.92	0.09	0.56	0.10

*Notes:****p<0.01, **p<0.05, *p<0.10. This table shows heterogeneous effects by gender, whether the student scored below the median in the 6th grade standardized exam, and by whether his or her mother completed middle school or less. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. All regressions control for school cut-off fixed effects.

Table A10: Heterogeneity by Differences in Teacher-Student Ratio

	Spa HS	Math HS	GPA	Failed	Delayed	No Cert.	Perseverance	Time	Aspire Coll.	Frac Voc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$1\{score \geq cutoff\}$	0.033	0.008	-0.193***	0.047***	0.027***	0.022***	-0.090*	-0.081**	-0.025**	0.008
	(0.027)	(0.027)	(0.042)	(0.016)	(0.008)	(0.007)	(0.046)	(0.036)	(0.011)	(0.008)
$1\{score \geq cutoff\} * \triangle$ teacher-student ratio	0.978	1.742	2.304	0.627	0.724	0.848	1.665	-0.785	-0.711	-0.456
	(2.238)	(2.200)	(3.536)	(1.327)	(0.681)	(0.607)	(4.244)	(3.204)	(0.902)	(0.773)
Observations	31785	31785	32181	32181	32181	32181	13496	17795	32181	32181
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean LHS	0.02	0.03	7.99	0.23	0.03	0.04	0.07	0.04	0.87	0.24

Notes: **p<0.01, **p<0.05, *p<0.10. This table shows heterogeneous effects by the difference in teacher-student ratio between morning and afternoon shift. All regressions control for school cut-off fixed effects and include controls. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level.

Table A11: Effects by Cut-off Type

	(1) Mor. shift	(2) Peer Grades	(3) HS Exam	(4) 8th GPA	(5) Failed	(6) No cert.	(7) Perseverance	(8) Aspire College	(9) Frac. Voc.
Panel A. Shift Cut-offs									
$1\{score \geq cutoff\}$	0.679***	0.625***	0.019	-0.206***	0.041***	0.014***	-0.101***	-0.019**	0.012**
	(0.016)	(0.024)	(0.016)	(0.030)	(0.011)	(0.005)	(0.028)	(0.008)	(0.006)
Observations	32181	32181	31785	32181	32181	32181	13496	32181	32181
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean LHS	0.30	0.14	0.04	7.99	0.23	0.04	0.07	0.87	0.24
Panel B. Facility Cut-offs									
$1\{score \geq cutoff\}$	-0.406***	0.386***	-0.022	-0.077**	0.036**	0.003	-0.124***	-0.003	-0.008
	(0.027)	(0.029)	(0.022)	(0.039)	(0.015)	(0.008)	(0.041)	(0.011)	(0.008)
Observations	18020	18020	17777	18020	18020	18020	6910	18020	18020
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean LHS	0.59	0.01	0.01	8.02	0.21	0.05	0.09	0.88	0.23

Notes: ***p<0.01, **p<0.05, *p<0.10. Panel A replicates results shown previously using cut-offs created within facilities. Panel B uses cut-offs created across facilities. All columns show results for a bandwidth of 5 points within the cut-off. All regressions control for cut-off fixed effects. Controls include gender, age, mother's education, 5th grade standardized test scores, lives close to school, has siblings in school, primary school shift, attended a private primary school. Heteroskedasticity-robust standard errors are in parenthesis. Standard errors adjust for clustering at the attended middle school level.

B Data

Five sources of data are used in this study: school assignment data and the corresponding demographic questionnaire, data from standardized tests in 7th grade and 8th grade, data from the high school placement exam and background questionnaire, administrative data linked to high school applicants, and school-level data. Below I describe how each variable was constructed and whether it was asked in all survey rounds.

Individual-level matching of the data sets was completed through the national identification number (CURP) and in rare cases, if the number was not reported, it was made on the basis of complete name and date of birth. Merges are restricted to the first appearance in the high school database.

- **IDANIS Exam**: The (IDANIS) is an ability exam implemented since 1989 for students' transition from primary to lower middle school. The multiple-choice test is applied to 6th graders at the end of the school year and has a maximum of 60 points. The exam is crafted as a diagnostic tool for basic skills rather than a knowledge test. The test focuses on three areas: use of mathematics, abstract reasoning and communication. Exams are implemented by SEP officials and graded by optical mark recognition machines.

- **Middle School Application Questionnaires**: Students seeking to enroll in lower middle school in Mexico City complete a form at the beginning of the year that includes information on their date of birth, their address, disabilities, whether they speak an indigenous language, their first, second and third school option, whether they have siblings in their first-option school, and parental level of education.

- **ENLACE:** The *Evaluacion Nacional de Logro Academico en Centros Escolares* or ENLACE is a standardized exam that previous to 2013 was applied to all students enrolled in private and public primary and middle schools. The test was designed to examine student's math and Spanish achievement. A third subject was tested in alternating years. The exam is composed of approximately 50 multiple-choice questions for each subject, with scores ranging from 200 to 800. The exam was applied to all students in Mexico and was discontinued in 2014.

- **PLANEA:** The Plan Nacional para las Evaluaciones de los Aprendizajes (PLANEA) is a standarized test score applied in June 2015 to a sample of students enrolled in 9th grade. Unlike ENLACE, PLANEA is not a censal exam but rather is applied to a random sample of students in each school. The results of the test are presented as levels of achievement (1-4). The information of this exam is used to compare levels of attrition across different datasets.

- **Adult Education Rosters:** Middle school is offered to students up to 15 years of age. If students would like to return to school later on to complete their basic education, they can enroll with *Instituto Nacional para la Educacin de los Adultos* (INEA). The rosters that contain the names of enrolled students are publicly available and can be found online ($http://www.inea.gob.mx/transparencia/Beneficiarios_2016.html$).

- **High School Questionnaires and Exam:** Admission to public high schools in Mexico City is done through a competitive admission process. A consortium of nine different schooling systems (the Comision Metropolitana de Instituciones Publicas De Educacion Media Superior or COMIPEMS) manage this process jointly to coordinate admissions. The documents that students need to complete to register are composed of two parts: (i) a questionnaire that is used for research purposes and that asks students questions about their background, experiences in middle school and aspirations and (ii) the form where students can list up to 20 high school choices. High school tracks are divided into vocational, technical and general. Students can select a combination of either track (and for vocational and technical, they can also select the specific area of specialization). Because most students select the general (academic) track, to increase power I combine the vocational and technical schools into a single category. While the elite IPN high schools are officially technical schools, I exclude them from this category, because their focus is academic (for instance, there is a positive correlation between grades and selecting IPN schools and a negative correlation between grades and selecting any other type of vocational/technical schools). In addition, because IPN high schools have minimum GPA requirements, I wanted to rule out the possibility that the effects were driven by students choosing schools on the basis of

their likelihood of admission. The high school examination comprises 128 multiple-choice question testing different subjects of the middle school curricula (Spanish, math, history, geography, physics, verbal ability and mathematical aptitude). Details of the assigned mechanism for high school can be found in Dustan et al. (2016).

- **911 Questionnaires:** The 911 questionnaires are school-level questionnaires reported through each school and collected by the SEP. These data are reported by principals and collected at the beginning and at the end of each academic year and contain information on the number of students, personnel, teachers, classrooms and family expenditures in education.

- **School Census**: In 2013 the SEP, in coordination with the National Statistics Office, conducted a national school census. The publicly released data contain information on building characteristics and GPS coordinates for all schools in the country.