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Learning About Opportunity: Spillovers of Elite School Admissions in Peru

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This paper studies how the admission of a student to an elite school changes the schooling outcomes of younger cohorts in the student's origin school in Peru. Using a sharp regression discontinuity design, the analysis finds that the admission of an older schoolmate increases the probability that students in origin schools will apply and gain admission to the same elite school system. The effect is concentrated among students whose parents have low education levels, which indicates a process of information diffusion. Furthermore, there is a slightly positive effect on the learning achievement of potential applicants and no negative effect on the learning of students who are ineligible to apply. Overall, the findings show that selective schools can have effects that go beyond their own students and indicate that role models can be an effective mechanism for increasing the demand from high-achieving, low-income students for high-quality education.

JEL codes: D83, I21, I24.

KEYWORDS

elite schools, education inequality, education externalities, information diffusion, peer effects, school choice.

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Oportunidades a la vista: Externalidades de escuelas de élite en Perú

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Este estudio analiza cómo la admisión de un estudiante a un sistema de colegios públicos de alto rendimiento en Perú cambia los resultados educativos de estudiantes más jóvenes que acuden a la misma escuela de origen que el estudiante en cuestión. Utilizando un diseño de regresión discontinua para la identificación de un efecto causal, el análisis muestra que la admisión de un estudiante a un colegio de alto rendimiento aumenta la probabilidad de que, posteriormente, alumnos más jóvenes de la misma escuela postulen y sean admitidos al mismo sistema de colegios de alto rendimiento. El efecto se concentra en los estudiantes de familias de menor estatus socioeconómico (ESE), medido por la educación de la madre, lo cual sugiere que la difusión de información tiene un rol crucial para explicar los resultados. Asimismo, se encuentra evidencia sugestiva de un ligero efecto positivo en el logro académico de los postulantes potenciales; y no se encuentra ningún efecto negativo en los aprendizajes de los estudiantes que no son elegibles para postular a este sistema de colegios. Los hallazgos de este trabajo muestran que las escuelas selectivas pueden tener efectos que van más allá de sus propios estudiantes e indican que la disponibilidad de modelos a seguir puede ser un mecanismo eficaz para aumentar la demanda de educación de alta calidad por parte de estudiantes de alto rendimiento de menor ESE.

Códigos JEL: D83, I21, I24.

KEYWORDS
escuelas de élite, desigualdad educativa, externalidades educativas, difusión de información, efectos de pares, elección de escuela.

1 | INTRODUCTION

Elite schools—a common feature of educational systems across the world—are often seen as an important policy tool for improving the access of high-achieving, low-income youth to high-quality schooling. Yet, several studies have documented that talented students from poorer families apply less often to elite schools than those from better-off families, even when the schools offer low or no fees, scholarships, and the ability to apply regardless of how far a student lives from the school (Pathak and Shi, 2014; Abdulkadiroğlu et al., 2017; Pathak, 2017; Abdulkadiroğlu et al., 2018, 2020).[1] This demand gap could be caused in part by students from disadvantaged backgrounds lacking enough information about the benefits of elite schools and application processes—including admission probabilities—and that lack might be more pronounced among youth living in areas and attending schools that have traditionally not sent students to elite institutions.

Addressing demand-side inequalities requires close attention to the diffusion of information about elite schools among high-achieving, low-income youth. Older peers are an important channel of information diffusion. A student's admission to an elite school can influence the schooling decisions of the student's younger peers in the origin school—particularly peers from disadvantaged backgrounds—by boosting information diffusion on the benefits of elite schools and application processes, including admission chances. The students may also serve as role models to younger students and help them determine whether elite schools will provide a good match for their needs and aspirations. Furthermore, better information about elite schools can improve student performance at lower educational levels, either through higher student effort or school inputs (e.g., if school principals and teachers focus on the learning and exam preparation of high-ability students). Such peer effects can motivate affirmative action programs or interventions providing direct support in educational decisions, for example through mentorship.

In this paper, we characterize the diffusion of information on a recently created system of elite schools by investigating the effects of previously admitted students on the applications, admissions, and learning outcomes of younger cohorts in their schools of origin. We argue that in our context previous elite-school admissions should not or should only marginally modify the costs of attending the schools and would mainly contribute to information diffusion and salience. We first ask if past admissions to elite schools have externalities on the applications and admission outcomes of current students. We then examine which children respond to the information shock and to what extent the effects persist over time. Finally, we ask whether past admissions also modify learning conditions and enrollment in the origin schools, therein affecting not only potential applicants but also other students.

We investigate these questions in the context of the rapid establishment and expansion of a nationwide system of highly selective secondary schools in Peru. The public *Colegios de Alto Rendimiento* (COAR) system of boarding schools is targeted to high-performance students enrolled in public schools and provides high-quality teaching, mentorships, and additional activities (e.g., arts, sports, and personal development). COAR started in 2015 with 14 schools and 1,600 students, and by 2017 there were 24 COAR schools and 2,700 students. COAR offers grade 9 to grade 11 education and only accepts applications from grade 8 students with the highest GPA in their school—up to 3 students per school before 2017 and up to 10 since.[2] Basurto, Zárate and Barron (2020) examine the effects of attending COAR and find that it increases the likelihood of university enrollment, which indicates that COAR's higher inputs produce long-term benefits.

[1] See also Hoxby and Turner (2015) and Hoxby and Avery (2013) for university enrollment in the United States.

[2] Regular secondary schools in Peru offer grade 7 to grade 11 education and hence students who apply to COAR in grade 9 and are not accepted stay in their origin school for the remaining of their studies.

To estimate the causal effect of a student's COAR admission on younger schoolmates' outcomes, we use a regression discontinuity (RD) design based on the local experiments generated by the centralized admissions process. This process consists of a standardized exam (in math and literacy) and subjective evaluations of socioemotional skills through interviews and group activities, and the results are combined to produce an admission score. The admission process combined with the high demand for COAR schools generates an admission cutoff score for each of the 24 administrative departments in which Peru is organized. Intuitively, we compare outcomes in schools where previous applicants were marginally admitted with outcomes in schools where previous applicants were marginally rejected.[3]

In terms of results and mechanisms, a first channel can be discarded early on. The admission of a former schoolmate may help students to gain insight into the application process (e.g., specifics about evaluations or logistics), which would directly decrease their application costs or improve their admission chances. This channel is nevertheless unlikely to explain our results. Schoolmates of an older student who was marginally rejected from COAR can access the same information about the application process as those whose schoolmate was marginally accepted. The only difference between the applicants above and below the admissions cutoff is a marginally different score.

Even though COAR schools are advertised through a dedicated website and media outlets, schoolmates of a student admitted to COAR might learn more about COAR schools' attributes (e.g., the quality of education, safety of their locations, etc.) and, perhaps more importantly, about whether the elite schools might be a good option and distinct possibility for them. In practice, students could learn about COAR either through direct interactions with their former schoolmate or indirectly, such as through school principals and teachers. Access to student role models and information should be particularly useful to potential applicants who have less familiarity with COAR schools. We expect that youth from a lower socioeconomic status are more likely to lack information on COAR schools. Some students might also be overly pessimistic about their admission chances and, following previous admissions, update their related perceptions.

Consistently, we find that last year's admissions in a school significantly increase current COAR applications and admissions. The number of applicants increases by .48, which is 20% of the mean of 2.45 applicants in schools below the cutoff. Admissions depend not only on students' applications, but also on their preparation and efforts. The number of admitted students increases by .25, or 47% of the mean of .54. The externalities of COAR admissions on applications of next cohorts seem to persist, with attenuation, after 2 years. Furthermore, we observe that externalities also operate in nearby schools, albeit at a lower degree, with weaker effects of marginal admissions on students in other schools in the same administrative district.

Importantly, children from less-educated families seem to react more than other children to past COAR admissions. This finding corroborates the assumption that high-achieving children from such backgrounds have less access to information about this school system and are more likely to update their beliefs about COAR in reaction to an information shock.

COAR schools provide free tuition, boarding, and materials. Yet, children and families living further from COAR schools likely face higher costs of attending these schools, such as transportation expenditures and security risks, which are likely higher for girls. Our results also corroborate the role of such costs. Focusing on children with less-educated parents, the

[3] Because admission offers are made to individuals and we are interested in investigating school-level outcomes, we define as our treatment of interest the admission to the COAR system of an origin school's highest-ranking applicant. This definition generates a sharp discontinuity in admission probabilities at the school level.

effects of previous admissions are high for children enrolled in schools near COAR schools, but small and not significantly different from zero for children in schools that are further away. Along the same lines, previous admissions affect the applications of girls only when there is a COAR school nearby. The admission to COAR of an older schoolmate could also directly modify students' benefits and costs of attending COAR by expanding the network that students have in this school system, which we speculate should be more valuable to students living further from COAR schools. Our results indicate that these effects should be modest, though, at least among low-income youth and women. Hence, the analysis confirms that the costs of COAR attendance are intermediating the effects of information diffusion.

We further investigate whether the effect of past COAR admissions on current application decisions in an origin school is stronger among youth who belong to a specific gender.[4] We do not find this to be the case, which suggests that information diffusion and role-model effects in this context are not associated with reference groups such as gender.

Beyond applications, the treatment under analysis could shape student learning by changing the efforts expended on studying or the school inputs that potential COAR applicants receive. For example, motivated by the admission of one of their students, school principals and teachers may devote time and effort to helping the next generation of COAR applicants in their school, which in turn could potentially affect other students' learning. We use information from a national standardized test (ECE, from the Spanish) to investigate, with a reduced-form approach, the potential effects of changes in student and teacher efforts on the learning of top students and other students. We find that following a schoolmate's COAR admission, new applicants have on average a lower class rank (measured by their GPA). Hence, past COAR admissions result in a more numerous and less-well-ranked pool of applicants. However, they do not perform significantly less well on the ECE or COAR application exam. Together, these findings suggest that past COAR admissions could slightly improve the preparedness and learning achievement of potential applicants.[5]

When we study the achievement of other students, we do not observe a significant impact in the median or the 25th percentile of the ECE score distribution in the school. This indicates—encouragingly—that there is no negative externality on the learning achievement of other students, which could occur if school principals and teachers reallocate teaching efforts from low- to high-ability students.

Finally, we study changes in enrollment in origin schools due to previous COAR admissions by their students, speculating that such changes could occur if COAR admissions work as a signal of school quality. However, we do not find evidence of changes in the demand for origin-school enrollment. So, at least in the short term, the success of schools in sending some of their students to COAR does not generate an inflow of new students.

We contribute to three broad pieces of literature. First, we contribute to the literature on the demand for school quality and related inequalities. A rich literature in economics and sociology has documented that poorer high-achieving students tend to have less-ambitious aspirations and application behaviors than richer high-achieving students. This pattern may be due to heterogeneous preferences—families often place more weight on school proximity than school quality (Black, 1999; Bayer et al., 2007; Deming et al., 2014; Chumacero et al., 2011) or financial constraints. But the pattern also often seems to result from differences in perceptions of the value of higher-quality education (Boneva and Rauh, 2017; Belfield et al.,

[4] We do not have the data to do the same exercise by parental education because this information was not collected in the COAR admissions in 2015.

[5] Bedoya et al. (2019) use a subsample from one cohort in our data and find that last year's COAR admissions in a school decrease ECE test scores in math in that school the following year (with no effects in literacy and history). However, this result is not consistently significant across their specifications.

2020). Centralized admission systems can make it easier for disadvantaged applicants to access better schools; however, students still need to well be informed about the application process and schooling choices, which is not always the case (Chen and Pereyra, 2019; Kapor, Neilson and Zimmerman, 2020).[6] We contribute to this literature by considering a context where the monetary costs of attending elite schools are minimal (tuition and board are provided for free) and information on new opportunities in elite schools is progressively diffusing. While unable to sort out the exact information content of the signal (e.g., quality and costs of schools, beliefs about own academic ability and future opportunities), we confirm that access to information, in particular through older peers, is an important determinant of the demand for elite schools. Such effects can drive persisting inequalities in demand across schools and localities. We also show that even with minimal direct costs, indirect costs associated with distance (e.g. transportation and security) continue to constrain decisions.

Second, and relatedly, we contribute to the literature on interventions to improve the school choices of students from poorer backgrounds. The studies that evaluate information interventions about school quality usually find positive effects (Hastings and Weinstein, 2008; Koning and van der Wiel, 2013; Friesen et al., 2012), but not always: Mizala and Urquiola (2013), for example, find no effect of publishing a measure of school quality in Chile. In a recent study, Carlana, Ferrara and Pinotti (2018) evaluate an intervention which combines information with mentoring to high-achieving immigrants in Italy and find positive effects (students make more ambitious track choices).[7] Our results confirm that interventions based on role models can enhance access to information and incentivize high-ability adolescents to gain access to better schooling.

Third, we contribute to the literature on the benefits of elite secondary schools. A string of studies has focused on the direct effects of elite schools, that is, the benefits students derive from attending these schools (Ding and Lehrer, 2007; Jackson, 2010; Pop-Eleches and Urquiola, 2013; Abdulkadiroğlu et al., 2014; Estrada and Gignoux, 2017). We extend this work by looking at the externalities of elite schools. Specifically, we document how elite school admissions generate changes in application behaviors and learning outcomes among children in lower schooling levels, including the potential externalities on the learning achievement of youth who are ineligible for elite school admissions. We find that previous admissions enhance educational ambitions, and maybe efforts, among pupils eligible to elite schools and do not seem to hurt ineligible ones.[8] Furthermore, we study whether admissions to elite schools change enrollment in the schools whose students succeed in gaining elite school admission, but find no evidence of such effects in our time frame (1 to 2 years).

The rest of the paper is organized into the following sections. Section 2 documents the institutional context. Section 3 presents the data. Section 4 describes our empirical strategy. Section 5 reports the main results and Section 6, the evidence on mechanisms. Section 7 presents evidence on additional—indirect—effects, and Section 8 concludes.

[6] Relatedly, sociologists have recently insisted on students' heterogeneous abilities to access and process the information on the value of education and make informed choices (Olivier et al., 2018).

[7] Goux, Gurgand and Maurin (2016) study an information intervention targeted to lower-ability children in France and find that it makes their school choices more realistic—i.e., less overambitious.

[8] A strand of papers has documented that changes in university admission processes produce externality effects on secondary-school students, for example, through affirmative action policies (Page and Scott-Clayton, 2016; Thibaud, 2020) and scholarships (Angrist and Lavy, 2009; Kremer et al., 2009; Laajaj et al., 2018). However, no such evidence exists for lower levels of education. Another related literature documents the demand spillovers of older siblings on younger siblings; see, for example, Dustan (2018) on secondary schools in Mexico and Altmejd et al. (2020) on tertiary education in Chile, Croatia, Sweden, and the United States.

2 | INSTITUTIONAL CONTEXT

2.1 | The COAR School System

The COAR system caters to high-performance secondary students and is managed by the Peruvian Ministry of Education (MINEDU, from the Spanish). COAR offers boarding schools for the last three grades (out of five) of secondary education. COAR follows both the national curriculum and an international curriculum (the International Baccalaureate program). The pedagogical model has a focus on integral development and aims to complement high-quality teaching with a strong offering of mentorships and arts, sports, and personal development activities. Students board for 40 weeks per year and can visit relatives on the weekends. Tuition, boarding, and materials, including a laptop, clothing, and books, are free of charge. MINEDU estimates that the average cost per pupil in COAR is around twice as much as the cost in other secondary schools.

After COAR began in 2015 with 14 schools and 1,600 students, it expanded to 22 schools and 2,400 students the following year, and the year after it met its goal of having one COAR school in each of Peru's 24 administrative departments, with 25 schools—Lima has two—and 2,700 students (see Table 1). The increase in supply has been met with an increase in demand. Applications to COAR soared from 6,300 in 2015 to 27,100 in 2018. The highly selective nature of COAR schools is reflected in their share of total enrollment in public schools: around 0.7% in 2018.

Applications to COAR are limited to public school students, who account for 77% of grade 8 enrollment in Peru and tend to be poorer than students enrolled in private schools. The outside option students have, if they do not get admitted to COAR, is to continue upper secondary education in the same public school they attended at lower secondary grades—or they could transfer to another public or private school.

2.2 | Admissions Process

COAR admissions are centralized and determined by applicants' performance on admissions assessments and department of residence. Applications are open to public school students ages 15 and younger who are enrolled in grade 8, have a GPA of at least 15 (on a 20-point scale), and are among the top 10 students (top 3 until 2017) in their school.[9]

From December to about mid-January of every year, students may apply, which requires written authorization from a parent or guardian. The applications, which are initially processed by the origin school's principal, include a student's top two ranked choices of specific COAR schools. One of the two is automatically the COAR school located in the student's department of residence, while the second can be any other COAR school. If there is no COAR school in the department where the student lives, the student can select any two schools. The admission decisions do not depend on these choices, although the allocation to specific COAR schools does.

In late January, applicants take a standardized admissions test that assesses literacy and math skills. Applicants that score in the top half of candidates from each department are admitted to a second assessment round in early February. In this round, applicants are interviewed by COAR staff and participate in group activities designed to assess socioemotional skills. The final admission score is computed by weighting the results from the written test (50%), group activities (20%), and interview (30%).[10]

[9] Alternatively, students who have achieved a top-five position in any national competition organized by MINEDU can also apply to COAR.

[10] In 2015 and 2016, applicants had to submit a written essay worth 10% of the admission score, and the stan-

Applicants are ranked by their admission score within each department, with those in the first (q_d) position by department admitted to the COAR system, q_d being a predefined admissions quota for each department. Applicants in positions higher than q_d are re-ranked by their admission score on a national list. Those ranked in the first n positions on the national list are admitted to the COAR system, n being a predefined admissions quota. Applicants ranked in positions higher than n are put on a waiting list. A simplified version of this process was in place in 2015, when all admissions decisions were made using the department-level rankings (i.e., the sum of the department quotas, q_d, was equal to COAR's total capacity). The school to which a student is assigned depends on a set of rules that considers the student's choices, admission score, and department quotas.

The admissions results are published around mid-February, and the school year starts in March. If some applicants decline the admission offer, an equivalent number of admissions offers is made by order of candidates' rank on the waiting list. However, only a few refuse. In the years we analyze, only 2.4% of applicants declined an admission offer. The admission process generates sharp discontinuities in admission offers that are amenable to an RD design.

3 | DATA

3.1 | Applications

We have microdata on COAR application and admission results for the years 2015 to 2019, which include the applicants' origin school, GPA rank within the origin school, and first and second choice of specific COAR schools. The administrative records also provide us with applicant's results on the admissions assessments, participation status in the second round of admissions, and final admission and enrollment decisions. Using this information, we construct the student's rank (within her department) in the admissions process. Students fill out a form from which we obtain basic sociodemographic information: gender, mother tongue, and parents' education level.[11]

Using the microdata, we construct a panel data set at the origin-school level with yearly applications and admissions outcomes. Linking students to schools is straightforward because the administrative records include MINEDU's official, unique school ID. The data set includes our main outcomes, which are the number of students from the school who apply to COAR, who make it to the second round, who are admitted, and who effectively enroll in the COAR system. For the school's applicant pool, we construct the average GPA rank,[12] and average COAR admission score, and we identify the top student's COAR admission score.

3.2 | Student Census Evaluation

MINEDU has administered the Student Census Evaluation (ECE, from the Spanish) to grade 8 students each year since 2015, with the primary purpose of measuring competence in literacy and mathematics. The ECE is a census evaluation that collects information about the level of student learning but has no bearing on students' GPA or graduation (i.e., it is a

dardized test was worth 40%.

[11] For 2015, we do not have information about their parents' education.

[12] We multiply the GPA rank by -1 so that an increase in this variable means an improvement in the profile of the students.

low-stakes test).[13] The assessment is held in November, close to the end of the academic year, 2 months before the COAR application process opens. Scores are standardized at the national level with a mean of 500 and an SD of 100.

We have access to individual-level databases for 2015 and 2016,[14] which correspond to the cohorts of students who can apply to COAR in 2016 and 2017. We construct the median score and the 25th percentile at the school level to analyze the effect of previous COAR admissions on the learning achievement of students who are unlikely to be eligible to apply to COAR. For the ECE 2015, we have access to the student identification numbers, so we identify which students applied to COAR in 2016 and study the effect of past COAR admissions on their learning achievement. We have ECE scores for 96.4% of 2016 applicants. We collapse these results at the school level. Finally, we link all these data sets using the school ID. We recover ECE scores for 99.35% of the schools that apply to COAR in 2015 and 2016 and track the 2016 applicants' ECE scores for 86.3% of schools that applied in 2015.

3.3 | School Enrollment and School and Locality Characteristics

We also have access to school-level enrollment in grades 7 and 8 from 2014 to 2017 from the school census that MINEDU carries out every year for our entire sample of schools. From MINEDU's school registry, we use the schools' locations to calculate the distance between each school with COAR applicants and the nearest COAR school.

For descriptive purposes, we use the 2009 poverty rate published by the Ministry of Economy and Finance at the district level[15] and obtain information about population size in the school's locality from the 2017 population census. We have these indicators for all the schools in our sample.

3.4 | Sample

We restrict our analysis to schools applying to COAR for the first time to more cleanly capture the impact of having a student admitted to this school system. More precisely, we focus on the first year that the school had at least one student admitted to the second phase of the admission process, which gives us a total sample of 4,038 schools. Table A.2 presents summary statistics for the full sample—see Column 1—and the sample in the bandwidth used for our main RD analysis—see Column 2.

4 | RESEARCH DESIGN

4.1 | Admissions Cutoffs

The admissions process described in Section 2.2 generates sharp discontinuities in admission offers around each department's cutoff. We define department d's cutoff (c_d) as the score of the lowest-ranking applicant in the department admitted to COAR—ignore for the moment offers made to applicants on the waiting list. Now, consider the admissions score of the lowest-ranking applicant admitted from the department-level ranking list (s_d, or applicant with ranking q_d) and the lowest-ranking applicant admitted from the national ranking list

[13] The test is taken in all public and private schools in the country with at least five students enrolled in grade 8.

[14] In 2017, MINEDU did not administer the exam because teacher strikes and meteorological phenomena shortened the academic year.

[15] Peru is divided into 24 departments and the Constitutional Province of Callao, 196 provinces, and 1,874 districts.

(s^n, applicant with ranking n). Then, we can define department d's cutoff as the lowest of these two scores: $c_d = \min\{s_d, s^n\}$.

For intuition, consider the marginally admitted applicant in a department with a low c_d cutoff (where low is $c_d < s^n$), that is, applicant with ranking q_d. Note that counterfactually decreasing that student's score to until position $q_d + 1$ results in losing admission to COAR, as the score is too low to be admitted using the national list. This is not the case for applicants with ranking q_d in departments with high c_d cutoffs (i.e., $c_d > s^n$). To not be admitted to COAR, such an applicant's score would need to counterfactually decrease below s^n, and hence this is the effective admissions cutoff in that student's department. In other words, departments with many good candidates will have some candidates admitted in the national list. Hence, the departmental cutoff score will be the cutoff of the the national list, which is lower than the cutoff of the departmental list. Departments with fewer good candidates will only fill the seats reserved at the departmental level, as their candidates cannot compete for the remaining seats at the national level, which have a higher cutoff. Hence, the departmental cutoff will be equal to the cutoff of the departmental list.

4.2 | Identification Strategy

We are interested in estimating the causal effect of COAR admissions on outcomes in the admitted student's origin school. For identification, we follow an RD design based on the sharp discontinuities in admission offers that are produced by the centralized admissions process to this school system. Because admission offers are made to individuals and we are interested in investigating outcomes at the school level, we define as our treatment of interest the admission to the COAR system of an origin school's best-ranked student in the admission process. Such definition generates a sharp discontinuity in admission probabilities at the school level. If a school's highest-ranking applicant receives an admission offer, then at least one student in that school receives an offer, whereas if a school's highest-ranking applicant does not receive an admission offer, then no student in the school receives an offer. More precisely, we estimate the following model:

$$Y_s = \alpha + \beta Admitted_s + \theta rank_s + \delta Admitted_s.rank_s + \epsilon_s \tag{1}$$

Where Y_s is an outcome of school s, $Admitted_s$ is an indicator variable that equals 1 if the highest-ranking applicant of school s is admitted to COAR and $rank_s$ is the rank in the admissions queue (normalised by the departmental cutoff) of the highest-ranking applicant of school s. Outcomes are measured at a period after the admissions decisions characterized in $Admitted_s$ take place. We estimate equation 1 in a sample of schools close to the admission cutoff, which we obtain using the optimal bandwidth algorithm developed by Calonico, Cattaneo and Farrell (2019). We present bias-corrected RD estimates and standard errors as proposed in Calonico, Cattaneo and Farrell (2019), Calonico, Cattaneo and Farrell (2018), and Calonico, Cattaneo and Titiunik (2014).

Figure 1 shows the number of admitted applicants per school by the admission rank of the highest-ranking applicant in the school. We focus hereafter—unless stated otherwise—on the school's first year of application to COAR and stack results from all admission years. As it is possible to observe, there is a sharp discontinuity in the number of admitted students per school at the COAR admission cutoff.[16]

[16] Figure 1 presents information on admission offers made during the first stage of the admissions process. Although, as discussed in Section 2.2, some students decline their admission offer, which leads to lower-ranking applicants receiving admission offers, the acceptance rate around the cutoff is very high (see Figure

4.3 | Validity of the RD Setting

The identification of causal effects in an RD setting is done under the assumption that treatment status close to the cutoff is as good as random (Lee and Lemieux, 2010). Given that admission offers are a deterministic function of applicants' scores and admissions quotas, it is hard to believe that applicants close to the admission cutoff can precisely manipulate their admission score and change their admission status. Still, we investigate the validity of our identification assumption by looking at the balance around the admission cutoff of a set of 10 baseline characteristics.

Figure 2 shows balance checks for six school characteristics: number of first and second round COAR applicants in the baseline year, student enrollment in grades 1 and 2 in the baseline year, whether the school is located in an urban locality, and distance (in kilometers) to the closest COAR school. Figure 3 shows balance checks for the following student and locality characteristics: whether the highest-ranking applicant in the school is a girl and whether the student is a native Spanish speaker, the district's population size, and its poverty rate. As expected, a visual inspection does not reveal a discontinuity at the admission cutoff in any of the 10 reported variables. Table 3 reports the corresponding RD estimates, which confirm this pattern. Overall, the magnitude of the RD estimates is small, and only one of the 10 estimates is statistically significant at the 10% level.[17] Hence, we find evidence that supports the identification assumption required to estimate a causal effect in an RD design.

5 | MAIN RESULTS

5.1 | COAR Applications and Admissions

Figure 4 shows the discontinuities in applications to COAR the year after at least one applicant from the same school was accepted or rejected with an admission rank close to the COAR cutoff. The four panels are A, an indicator that at least one student applied to COAR; B, the number of applicants; C, the number of applicants accepted to the second round of the admission process; and D, the number of applicants admitted to COAR. All panels show marked discontinuities at the admission cutoff, indicating that students apply and get admitted to COAR schools more frequently when previous-year applicants were successful. Table 4 shows the corresponding regression estimates. As seen in Column 1, there is no significant effect on the probability that at least one student in the school applies to COAR (although the point estimate is positive at 4.4 pts and this probability is already high, at 86%, in schools just below the cutoff). However, there is a .48 increase in the number of applicants, which is 20% of the mean of 2.45 applicants in schools below the cutoff (Column 2). Along the same lines, the number of applicants accepted to the second round increases by .30, or 26% of the mean of 1.14 (Column 3), and the number of admitted students increases by .25, or 47% of the mean of .54 (Column 4). The last row of the table reports the year-to-year change in the application outcomes in schools on the left side of the cutoff, that is, when previous-year applicants were rejected, and shows that the number of applicants does not diminish in these schools (Column 2). Together, these results suggest

A.1 in the Appendix). As Table A.1 shows, the discontinuity in the probability of effective enrollment in the COAR system at the admission cutoff is .892 (p-value is 0.000). Hence, although we report intention-to-treat estimates throughout the paper, they are very close to the actual treatment effects.

[17] Researchers also look at the density of the running variable around the cutoff to detect a discontinuity that would indicate the existence of manipulation in the running variable (McCrary, 2008). As our running variable is a ranked list, we can discard by construction the presence of such discontinuities. Furthermore, if we look at the density of the raw admissions score, we do not observe any discontinuity at the cutoff (see Figure A.2 in the Appendix).

that there is no significant discouragement effect after a (narrow) failure in the previous cohort of students, as there is no clear effect on the probability that at least one student in the school applies to COAR and the number of applicants does not decrease after a marginal rejection to COAR. Overall, last year's admissions in a school significantly increase the numbers of current applications and admissions to COAR.

5.2 | New Applicants: Selection and Performance

Figure 5 shows the discontinuities in different measures of achievement of the school's applicants 1 year after a student from that school was marginally admitted to/rejected from COAR for the first time. The figure's four panels are A, the mean GPA class rank of applicants (multiplied by minus unity, so that a decrease indicates that students have a lower relative GPA within their school); B, their mean score at the COAR admission exam (standardized with mean 0 and SD 1); C, the best admission score among them; and D, their mean score on the ECE national standardized test administered before COAR applications are submitted (standardized with mean 500 and SD 100). Panel A shows that applicants are less well-ranked in their school, but Panels B and C do not show any sharp discontinuity in their mean and maximum scores at the COAR exam, and Panel D reveals no changes in their ECE test scores. Table 5 shows the corresponding estimates, and the first column confirms that the average class rank of applicants is lower by .15 and statistically significant the year after at least one applicant from the school was admitted to COAR (the average applicant is ranked second in the class). This result though must be read together with the documented increase in the number of applicants. The estimates on the next columns show that the mean and maximum scores of these new COAR applicants are not significantly lower than those of applicants from schools with no previous admissions, nor are their ECE scores (the point estimates for scores are positive but not statistically significant). In other words, despite being more numerous and less well ranked on average, the new applicants do not perform significantly less well on the COAR exam or the ECE. Together, these results suggest that past admissions could slightly improve the preparedness and learning achievement of potential applicants to COAR schools.

5.3 | Further Temporal and Spatial Externalities

Table 6 examines whether the effects of COAR admissions on new applications and admissions persist after 2 years (the same outcomes as in Table 4, but observed 1 year later). Column 1 shows that after 2 years, there are more often applicants in schools that had a successful applicant, with a probability of .95 against .88 in schools below the cutoff. Columns 2 to 4 show positive point estimates for the number of applicants and admitted students, but these are of lower magnitude than the effects 1 year after admission and are not statistically significant. While attenuated, the externalities of COAR admissions on applications of next cohorts thus seem to persist after 2 years.

Tables 7 and 8 examine whether the externalities on applications and admissions operate beyond the admitted student's origin school and reach students enrolled in other—geographically close—schools. Hence, we study applications at the level of the administrative districts, from which there are 1,874 in the country. The outcome variables are similar to the ones in Table 4 but are defined at the district rather than the school level and only consider the outcomes from students of other schools in the same district. The running variable is the admissions rank of the highest-ranking applicant in the district. Table 7 reports balancing tests showing that a set of observable characteristics—similar to the one in Table 3—present no significant discontinuities with district-level marginal admissions. In

Table 8, Columns 1 and 2 show positive point estimates but no statistically significant effects on applications while Columns 3 and 4 show that previous-year admissions of students from other schools in the district increase the number of applicants getting to the second round and being admitted to COAR. Hence, the externalities to some extent seem to operate beyond the admitted students' origin school to students from other schools in the district.

6 | MECHANISMS

COAR admissions of applicants from the same school (or district) but from a previous cohort can affect the decisions of current students to apply and enroll in these schools (and their learning outcomes) through several channels, including the diffusion of information and related changes in aspirations and learning conditions. Our reduced-form estimates do not allow us to unequivocally disentangle the role of these channels. However, we can gain insights on their relative importance from evidence on student characteristics associated with low propensities to apply to COAR and heterogeneous effects of previous admissions.

6.1 | Information Diffusion

While COAR schools are advertised through a dedicated website and media outlets, students could obtain more detailed information about this new school system if an older schoolmate is admitted to it. Previous admissions can make the information on COAR schools more salient or provide additional information on their benefits, either through direct interactions with previous admittees or through teachers and schools. We do not have direct measures on how much information students have on COAR, but some groups of potential applicants are more likely than others to lack such information. Among them are children of parents with lower educational attainment, who might underestimate the benefits of higher-quality secondary schooling.

Table 9 reports correlations between COAR applications and a set of individual, family, and school characteristics. We present results for a subsample of grade-2 students for whom we can associate their ECE scores in November 2015 to COAR applications in early 2016 and who are potential COAR applicants (have a GPA above 15 and are among the top three students in their school). Column 1 shows partial correlations of COAR applications with student gender, maternal education (an indicator of secondary school attendance), and mother tongue, controlling for deciles of ECE scores and school fixed effects. Column 2 introduces school characteristics: their urban location, distance to the nearest COAR school (in kilometers), previous-year applications and admissions, and controls for department fixed effects. Both regressions show that children with less-educated mothers apply less often to COAR, by about 8 percentage points (Columns 1 and 2). While potentially associated with other factors (such as costs, see next section), this pattern suggests a lack of information on COAR's educational opportunities and their returns.

Table 10 investigates for heterogeneous effects of previous admissions by maternal education using as outcomes the applications from those students whose mother attended only primary school and those whose mother attended secondary (or higher) school. Columns 1 and 2 show that past admissions only increase applications significantly, by .44 (or 26% compared to 1.67 applicants below the cutoff), for children from less-educated parents. Similarly, Columns 3 and 4 show that the number of admissions only increases significantly, by .21 (or 75% compared to .28 admitted students below the cutoff), for the same group. The effects are not statistically significant due to the smaller sample size but also to the smaller magnitude of the point estimates for children from more-educated mothers. Under the assumption that previous admissions do not significantly modify the economic constraints on COAR applications and attendance, the finding that children from families with lower educational resources react more than other children to previous admissions indicates that high-achieving children from such backgrounds lack information about the benefits of COAR schools and/or about their admission chances.

6.2 | Costs of COAR Attendance

Student applications to COAR depend on student aspirations and information access as well as the costs of attendance, which may particularly discourage high-achieving, low-income students from applying. A COAR school's location relative to a student's home is a primary factor of these attendance costs, so children and families who live far from COAR schools might face higher attendance costs (e.g., higher transportation costs). We can deconstruct the data into subexperiments and estimate local treatment effects for different school subgroups by splitting the sample along the characteristic of interest. To compare these estimates, it is important to remember that the groups likely differ along other associated dimensions, such as family income or the characteristics of schools. Along these lines, Table 9 shows that students living furthest from a COAR school apply less than students who live closer to one—conditional on learning achievement and family background. However, these students may also have less access to information about the COAR system. The likely correlation between distance to the closest COAR school and both attendance costs and information about such schools makes it difficult to interpret heterogeneities on school location only.

For this reason, we investigate the heterogeneity of the effects of past admissions along both maternal education and distance to the closest COAR school. Figure 6 reports the RD estimates for the number of COAR applications by maternal education and terciles of distance from the current school to the closest COAR school. The effects of previous admissions are particularly high for children with less-educated mothers and enrollment in schools near COAR schools. The estimated effects are smaller and not significantly different from zero for the other groups, except marginally for children with more-educated mothers and enrollment in schools far away. This suggests that distance to COAR schools is associated with the costs of COAR attendance, and those costs condition the information generated by previous COAR admissions. In other words, the information channel is conditional on the costs of enrollment not being too high.

Another dimension that is potentially associated with enrollment costs is gender. The costs (e.g., in terms of perceived risks) of attending boarding schools that are further than regular schools are likely higher for girls than boys. Columns 1 and 2 of Table 9 report the partial correlations of gender with COAR applications. In both models, girls apply more often than boys to COAR by 8–11 percentage points. However, Column 3 shows that girls in schools located further from COAR schools also apply less often, while Column 4 shows that the pattern is less marked for boys (the magnitude of the interaction between distance to COAR in kilometers and the female indicator is -.0002415 with a p-value of 0.109). Figure 7 reports heterogeneous effects along gender and terciles of distance from the current school to the closest COAR school of previous admissions on the number of COAR applications. While the effects on boys' applications do not vary significantly with distance to COAR schools, previous admissions affect the applications of girls, by about .45, only when the COAR school is nearby. Again, this suggests that the costs of COAR attendance intermediate the effects of information diffusion.[18]

[18] Table A.3 in the Appendix shows that the effect of past COAR admissions on current applications is concentrated among boys, which decreases the gender gap in COAR applications—on average, there are 1.6 female applicants and 0.8 male applicants per school in the comparison group.

6.3 | Role Models

An information shock such as the one generated by past admissions can be multidimensional. It can provide information on the benefits and the direct financial and opportunity costs of a COAR education, thus modifying the perceived returns from attending elite schools. It can also convey new role models who can both make the information on COAR relevant and shape students' aspirations regarding their educational attainment and future jobs. Moreover, these different effects can vary across children from different areas and family backgrounds.

One way to study the relevance of role-model effects associated with specific reference groups is to look at the interaction between the characteristics of admitted students from previous cohorts and those of current applicants (although such heterogeneous effects can also reflect variation in which type of information matters). In particular, Table 11 investigates whether previous COAR admissions of girls (boys) differently affects girls' and boys' applications. We define separate local experiments by restricting treatment to the (past) marginal admission of girls (by considering the highest-ranking female applicant in the school). The estimates do not show a clear pattern whereby new applications come from children with similar characteristics as those of previously admitted peers. If anything, boys seem to respond indifferently from past admissions of both girls and boys, while girls tend to respond more from past admissions of boys.

Thus, we do not find support for the idea that peer effects are stronger when the admitted student is from the same gender as potential applicants. This is no evidence however of the absence of role-model effects. It is possible that the first-order characteristic that defines a reference group in this context is the school of origin rather than gender. But, again, we cannot disentangle the content of the information that comes with previous admissions.

7 | INDIRECT EFFECTS

If principals or teachers—encouraged by a student in their school being admitted to COAR—reallocate inputs toward potential COAR applicants, past admissions could generate negative externalities on the learning achievement of the other students in the school. Furthermore, if having a student admitted to COAR is a signal of school quality—as some anecdotal evidence indicates—COAR admissions can also modify enrollment in origin schools in the longer run.

7.1 | Learning Achievement of Other Students

Figure 8 and Table 12 examine the learning achievement of students in origin schools who are unlikely to qualify to apply to COAR. Using a composite score from the ECE, the simple mean of the math and literacy scores, we find that neither the median nor the 25th percentile in the school—the students whose scores are too low to qualify for COAR—are significantly affected by marginal admissions in previous years. This indicates the absence of negative externalities on the students who are not potential COAR applicants. We lack more complete information on school and family investments in the secondary education of these children, but if such changes are present, they do not translate into different learning achievements.

7.2 | Changes in Enrollment at Origin Schools

In the longer run, COAR admissions could modify the perceived value of enrollment in the origin schools and the demand for them, which in turn could change student selection and

COAR admission outcomes. Figure 9 and Table 13 test for effects of previous admissions on enrollment in the next year in the first two grades of secondary schooling in the origin schools—students can apply to COAR at the end of grade 8. We find no evidence of significant effects on enrollment in those grades. While more detailed information on applications would be required to delve further into these equilibrium effects, this suggests that at least in the short run, the success of some schools in sending students to COAR does not generate an inflow of students.

8 | CONCLUSIONS

We used administrative data to study the effects of past admissions to the elite COAR schools on applications and admissions to those schools as well as on learning outcomes of younger cohorts in origin schools. The results show that admissions to COAR in the last year increase the number of current applications (by 20%) and admissions (25%). We also find similar but smaller effects on applications two years after a COAR admission and on applications of students in other schools from the same administrative district. Importantly, the effect is concentrated among children from less-educated families. Given that previous admissions should not impact the economic constraints of COAR applications and enrollment, this suggests that previous admissions mostly boost the diffusion of information and change beliefs about the benefits of elite schools among high-achieving, low-income children. However, the results also show that the costs associated with distance constrain application decisions and intermediate the effects of information diffusion. In particular, the effects of previous admissions on low-income youth are significant (economically and statistically) only among those students enrolled in schools nearby COAR schools.

A similar story emerges from an analysis by gender. Among girls, previous admissions significantly affect only the applications of those living close to COAR schools, while distance does not affect applications from boys. Furthermore, the analysis shows that past COAR admissions slightly improve the preparedness and learning achievement of potential applicants and—importantly—do not negatively affect the learning achievement of students who are ineligible for COAR admission. Finally, we do not find evidence that success in sending a student to an elite school translates into changes in the short run in the demand for enrollment in origin schools.

A rich literature in economics and sociology has shown that even conditional on ability, low-income youth tend to have a lower demand for elite schools. This paper documents two mechanisms behind this demand gap: less information about the benefits of elite schools and higher indirect costs. On a positive note, the results presented here show that the admission of a former schoolmate to an elite school translates to higher demand for elite schools among high-achieving, low-income students. Access to role models can make a difference. Not all is positive though. Even when the direct costs of application and attendance are minimal, the remaining costs can keep high-quality education beyond the reach of some low-income students.

The externalities documented in this paper have several policy implications. First, to increase elite-school access for low-income, high-achieving students, it is necessary to reduce the remaining (indirect) costs, which notably include those associated with distance. The nature of these costs may vary by context, but in some cases, it could be worth exploring policies such as transportation subsidies, busing, and safe transportation interventions. Above all, it is important to account for the inequalities in the access to information on the application processes and benefits of elite schools and access to role models that contribute to a more precise understanding of these processes and benefits and how elite schools can be a good match for high-achieving, low-income youth. In this regard, interventions using role models to diffuse information on elite schools deserve particular attention. Furthermore, the use of positive discrimination policies in admission decisions could potentially increase the availability of such role models and counterbalance some of the remaining costs that impede talented low-income children from enrolling in elite schools.

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FIGURES

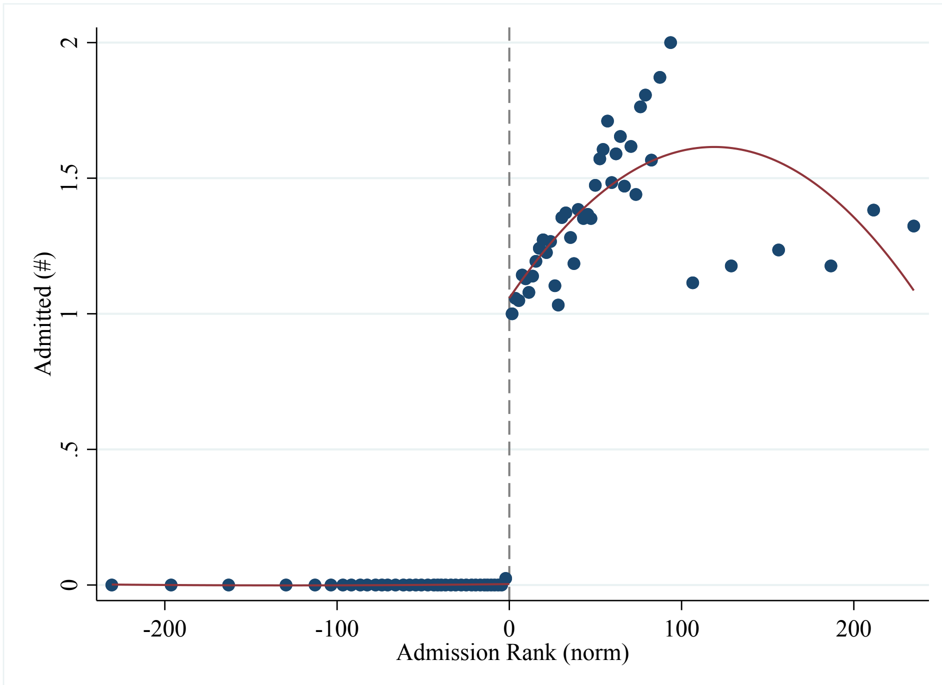
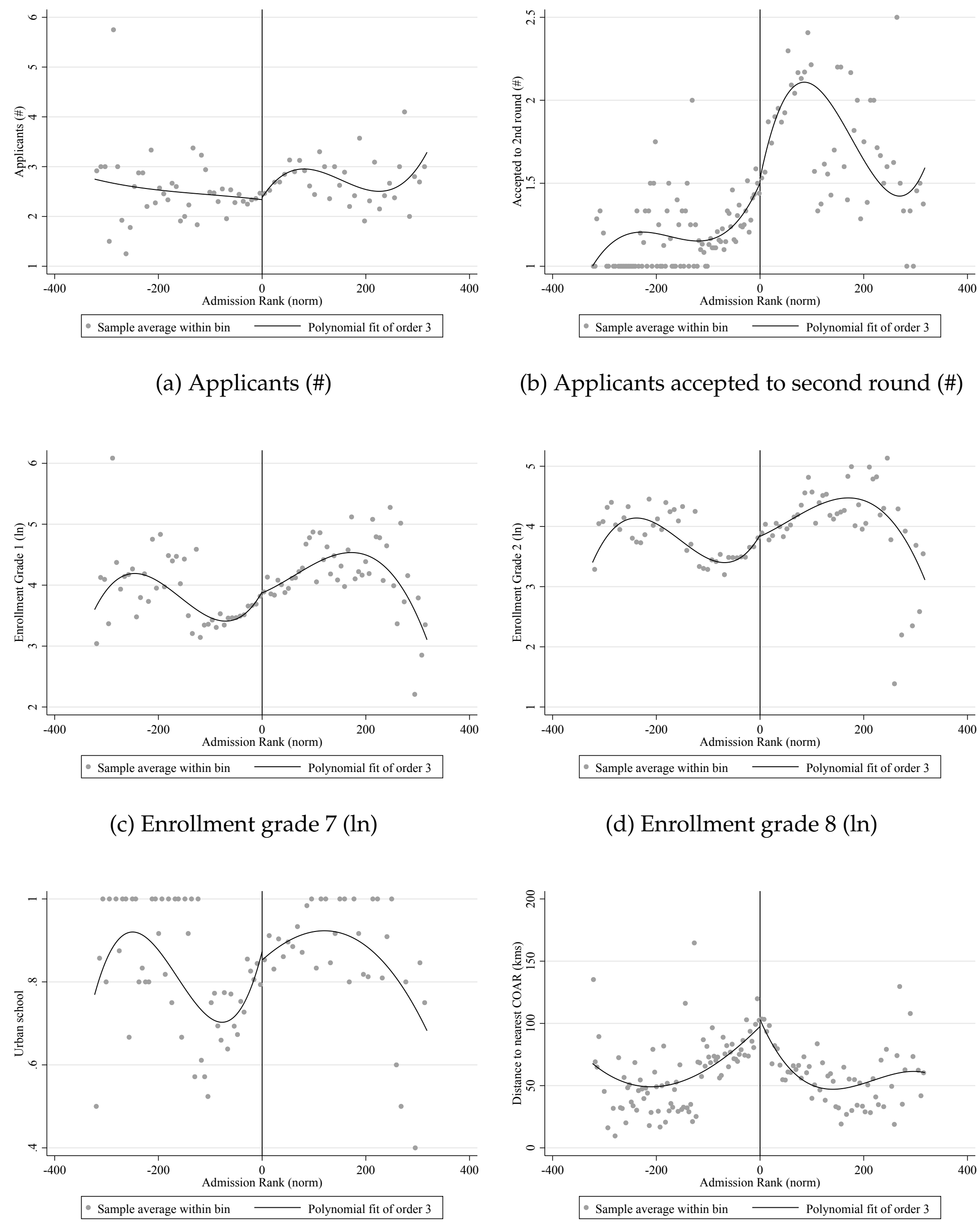


FIGURE 1 Number of Admitted Students by Admission Rank
Notes: The figure shows the number of students from one school admitted to COAR in year t as a function of the standardized admission rank of the highest-ranking applicant in the school in year t-1. The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the second-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-325,325). *Source:* COAR administrative data 2015–2018.



(a) Applicants (#)

(b) Applicants accepted to second round (#)

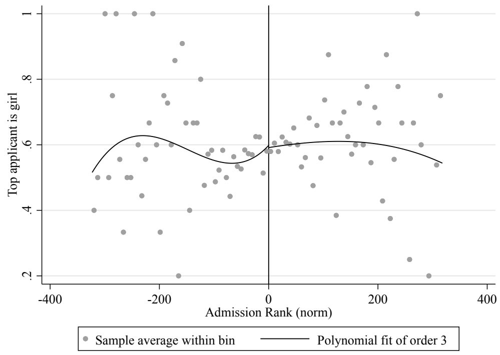
(c) Enrollment grade 7 (ln)

(d) Enrollment grade 8 (ln)

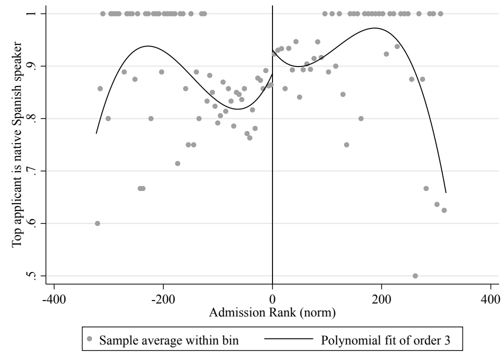
(e) Urban school

(f) Distance to nearest COAR (km)

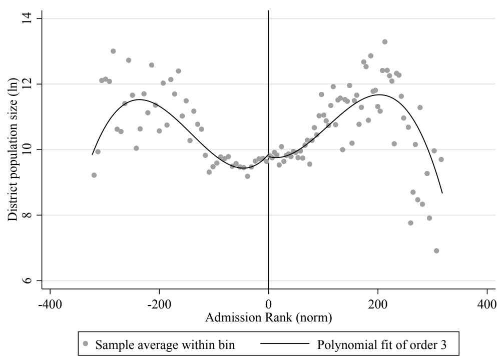
FIGURE 2 Balance of Covariates: School Characteristics.
Notes: The figure shows the conditional means of origin school characteristics by the standardized admission rank of the highest-ranking applicant in the school. The bandwidth of the bins used to estimate the local means are computed using the procedure developed by Calonico, Cattaneo and Titiunik (2015) to mimic the underlying variability of the data. The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-325, 325). The enrollment in origin schools is expressed in natural logarithms. We calculate the distance in kilometers between the origin school of the top applicant and the nearest COAR school, regardless of what department it is located in. *Source:* COAR administrative data 2015–2018; MINEDU school census 2016–2018.



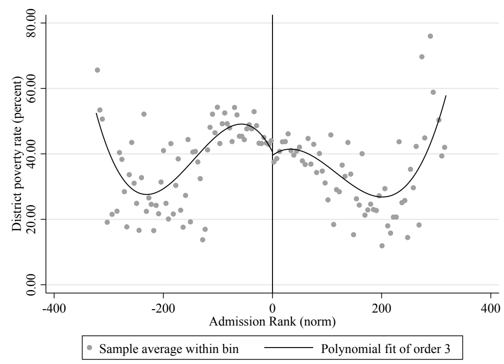
(a) Top applicant is a girl



(b) Top applicant is a native Spanish speaker

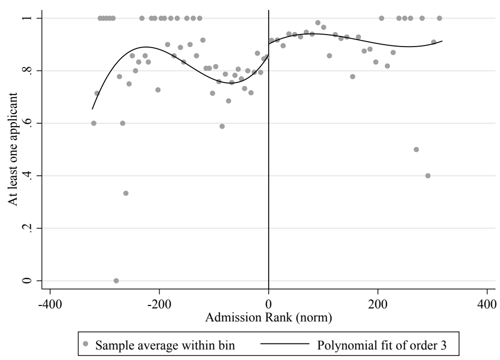


(c) District population

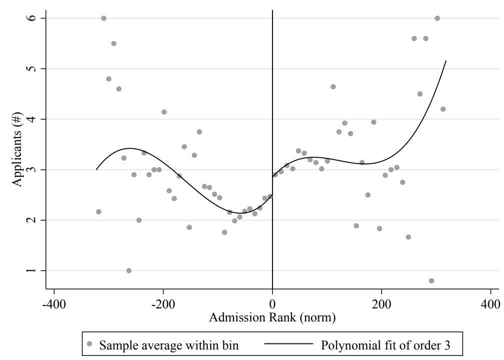


(d) District poverty rate (%)

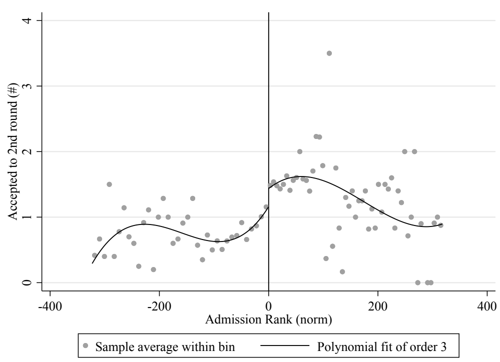
FIGURE 3 Balance of Covariates: Student and Locality Characteristics.
Notes: The figure shows the conditional means of student and locality characteristics by the standardized admission rank of the highest-ranking applicant in the school. The bandwidth of the bins used to estimate the local means are computed using the procedure developed by Calonico, Cattaneo and Titiunik (2015) to mimic the underlying variability of the data. The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2018; Ministry of Economy and Finance statistics; 2017 Population Census.



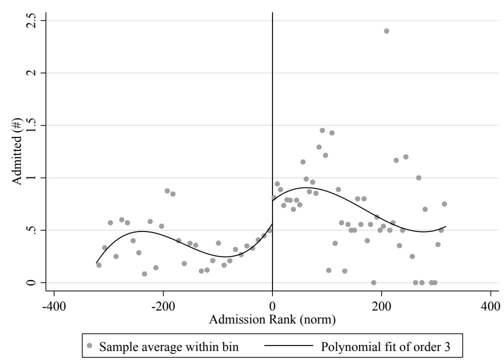
(a) At least one applicant



(b) Applicants (#)

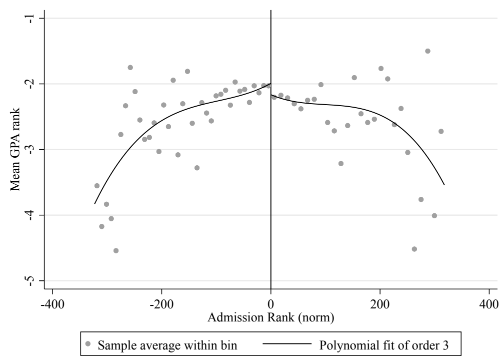


(c) Accepted to second round (#)

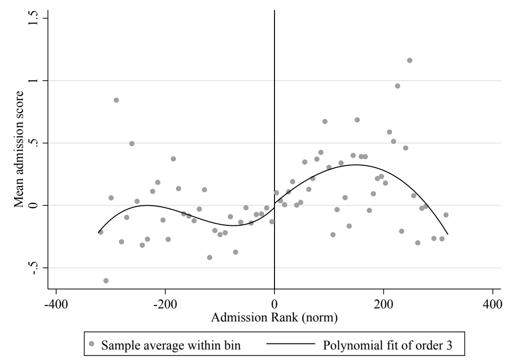


(d) Admitted (#)

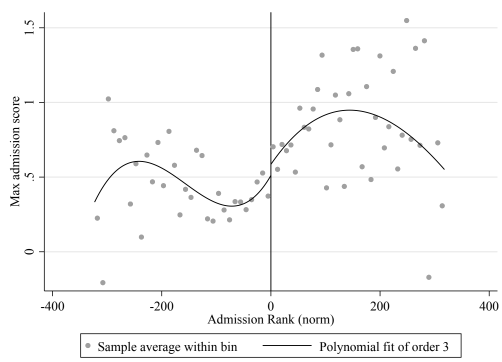
FIGURE 4 Applications in the Year Following an Admission.
Notes: The figure shows the conditional means of school-level applications to COAR in year t as a function of the standardized admission rank of the highest-ranking applicant in the school in year t-1. Observations are grouped in bins based on Calonico et al. (2017). The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time in year t-1. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2019.



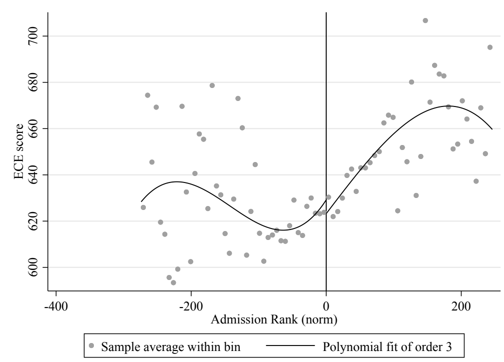
(a) Mean GPA rank



(b) Mean admission exam score

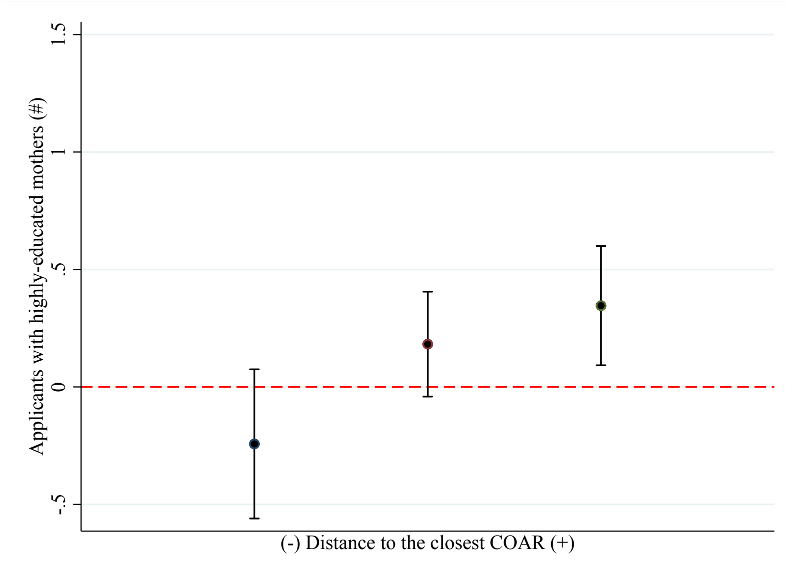


(c) Maximum admission exam score

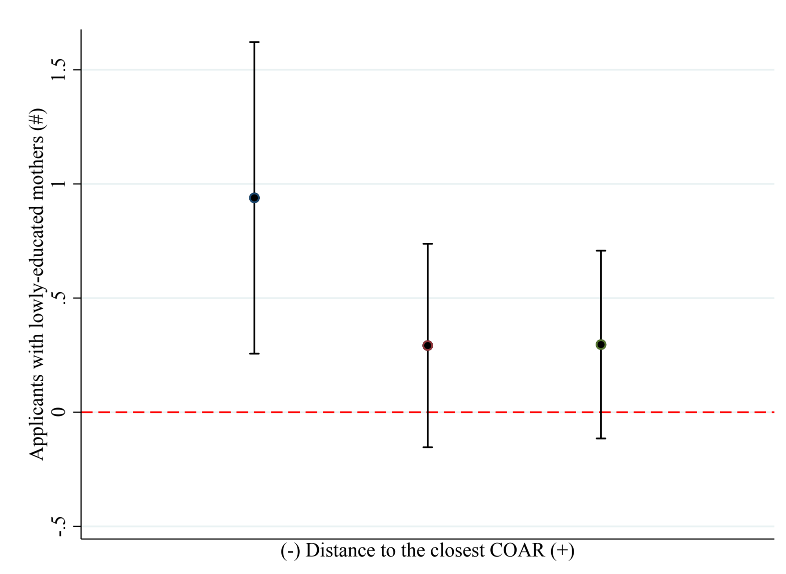


(d) ECE score

FIGURE 5 Applicant Pool Composition and Learning Achievements.
Notes: The figure shows the relationship between the learning achievement of COAR applicants in year t as a function of the standardized admission rank of the highest-ranking applicant in the school in year t-1. Panel A shows the average GPA rank (multiplied by minus unity, so that a decrease indicates that students have a lower relative GPA within their school); Panel B shows the average COAR admission exam score (standardized with mean 0 and SD 1); Panel C shows the highest COAR admission exam score; and Panel D shows the average score on the ECE held the November before students apply to COAR (standardized with mean 500 and SD 100). ECE scores are a simple average of language and math results. Observations are grouped in bins based on Calonico et al. (2017). The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time in year t-1. Panel D is also restricted to 2016 applicants. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2019; ECE 2015.

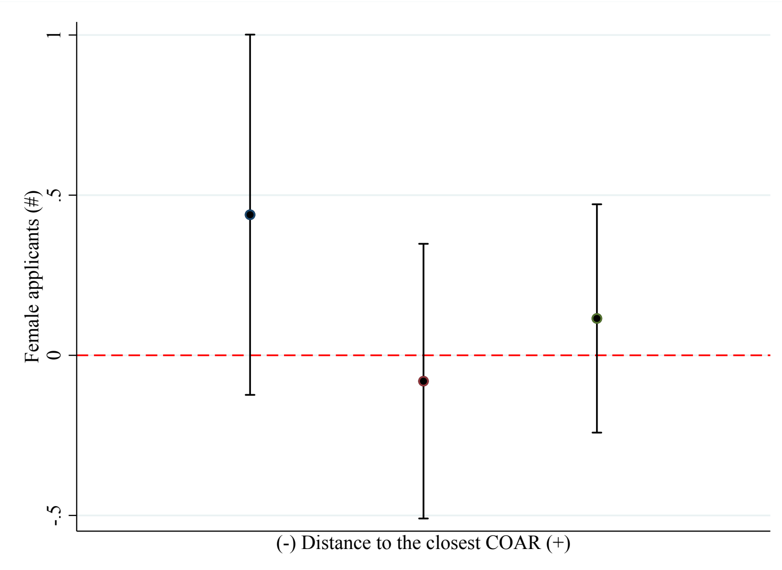


(a) Highly educated mother (#)

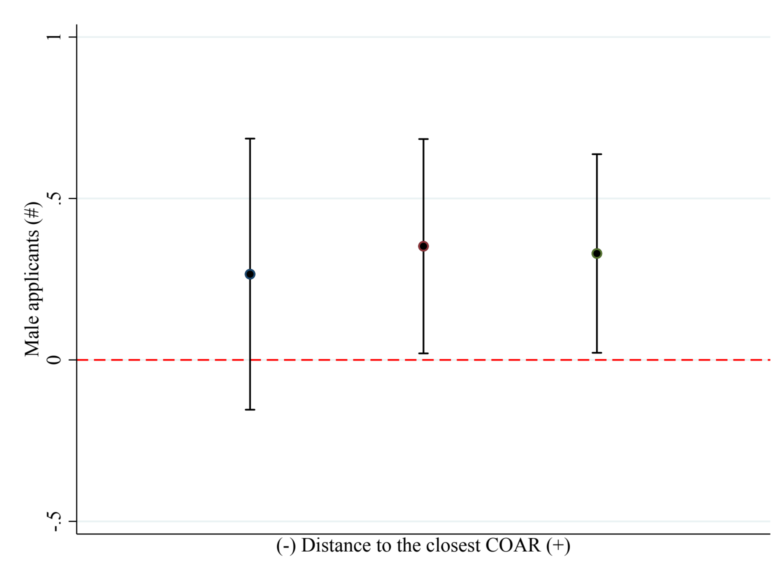


(b) Low-educated mother (#)

FIGURE 6 RD Estimates: Applications by Maternal Education and Distance to Nearest COAR (terciles).
Notes: The figures show the heterogeneity of the effect on the number of applicants in year t with highly educated and low-educated mothers by distance to the nearest COAR school. The distance in kilometers between the origin school of the top applicant and the nearest COAR school is calculated regardless to what department the school belongs. The sample consists of schools applying to COAR for the first time in year t-1 and is split into terciles of the distance to the nearest COAR school from applicants' origin school. The figures plot the corresponding point estimates and 95% confidence intervals. All estimates correspond to local linear regressions using the optimal bandwidth based on Calonico et al. (2017). The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2019; MINEDU school registry.

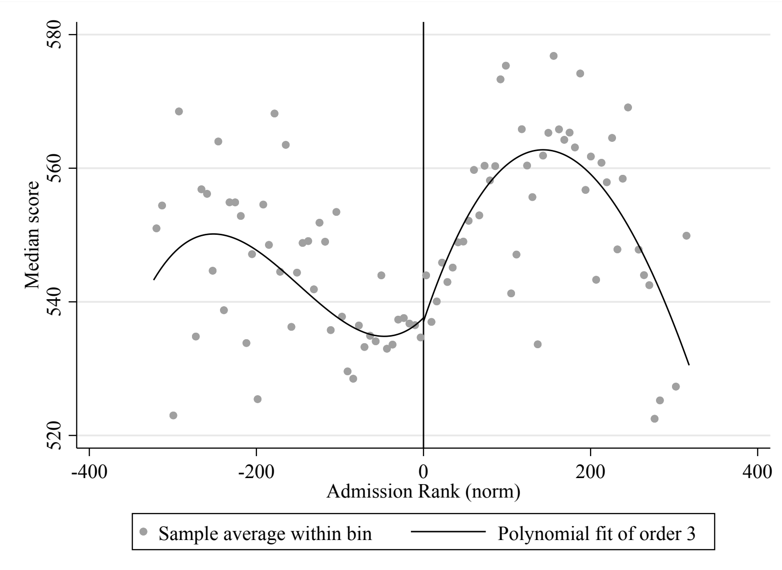


(a) Female applicants (#)

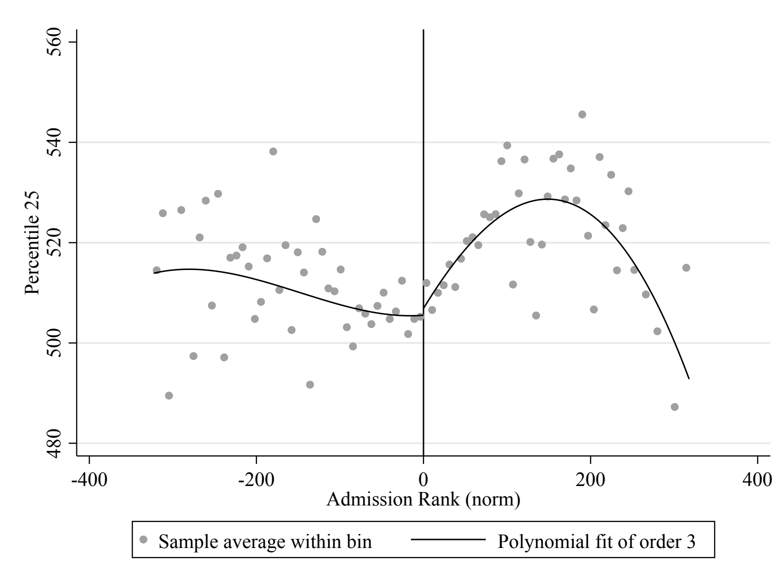


(b) Male applicants (#)

FIGURE 7 RD Estimates: Applications by Gender and Distance to Nearest COAR (terciles). *Notes:* The figures show the heterogeneity of the effect on the number of female and male applicants in year t by distance to the nearest COAR school. The distance in kilometers between the origin school of the top applicant and the nearest COAR school is calculated regardless of which department the school is located in. The sample consists of schools applying to COAR for the first time in year t-1. It is split into terciles of the distance to the nearest COAR school from applicants' origin school. The figures plot the corresponding point estimates and 95% confidence intervals. All estimates correspond to local linear regressions using the optimal bandwidth based on Calonico et al. (2017). The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2019; MINEDU school registry.

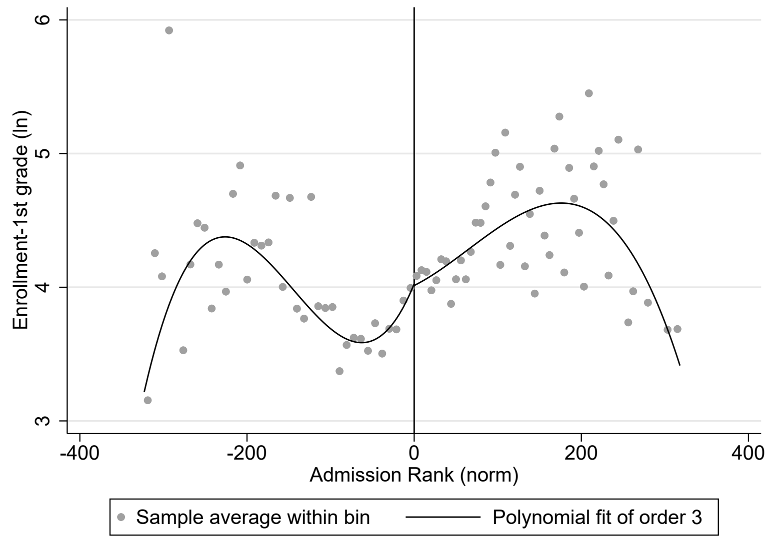


(a) Median

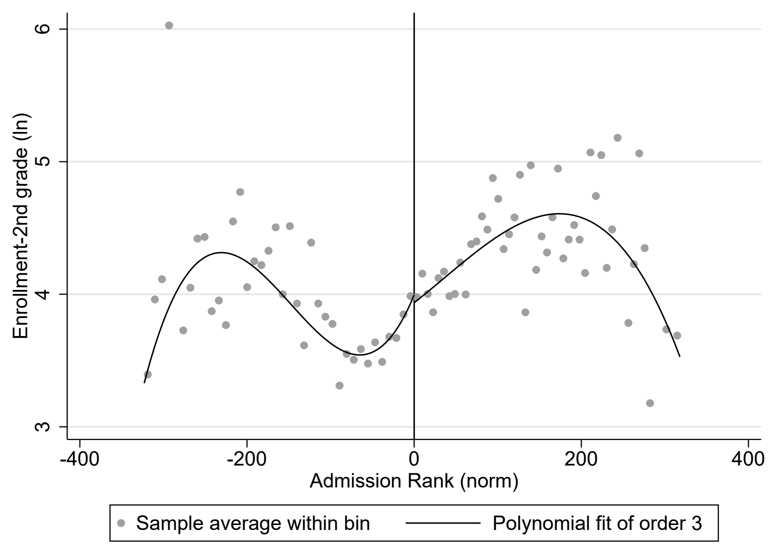


(b) Percentile 25

FIGURE 8 Learning Achievements of Grade-8 Students in Origin Schools
Notes: The figure shows the relationship between the learning achievements of grade-8 students who are unlikely to be qualified to apply to COAR as a function of the standardized admission rank of the highest-ranking applicant in the school in year t-1. Panel A shows the median, and Panel B shows the 25th percentile of the scores on the ECE held the November before students apply to COAR (standardized with mean 500 and SD 100). ECE scores are a simple average of language and math results. Observations are grouped in bins based on Calonico et al. (2017). The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of top-ranked students from schools applying to COAR for the first time in year t-1r. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2019; ECE 2015, 2016.



(a) Grade 7



(b) Grade 8

FIGURE 9 Enrollment in Origin Schools (ln).
Notes: The figure shows the conditional means of enrollment in grades 7 and 8 in origin schools in year t, a function of the standardized admission rank of the highest-ranking applicant in the school in year t-1. The enrollment in origin schools is expressed in natural logarithms. Individual observations are grouped in bins based on Calonico et al. (2017). The vertical lines separate schools with non-admitted (left side) and admitted applicants (right side) in year t-1. The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of the top-ranked students from schools applying to COAR for the first time in year t-1. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2019; MINEDU school census 2016–2018.

TABLES

TABLE 1 COAR Application Process and Enrollment Totals Against Origin-School Enrollments

	2015	2016	2017	2018
Applicants				
Students	6330	10403	25729	27161
Schools	3001	4514	5506	5641
Accepted to 2nd round				
Students	3307	5053	5659	5400
Schools	1990	2959	2321	2763
Admitted				
Students	1602	2412	2714	2701
Schools	1139	1646	1457	1668
Enrolled				
Students	1543	2352	2700	2687
Schools	1101	1604	1451	1665
Public school enrollment in t-1				
Grade 2	396242	393188	405757	412821

Notes: The table demonstrates the annual number of applications to COAR and the thinning of applications throughout the selection process and the final enrollment figures per year from 2015 to 2018. It also presents the number of schools where those students were enrolled in year t-1. The sample is unrestricted. The table also presents the number of students enrolled in public schools in grade 8 (the grade at the end of which students can apply to COAR). *Source:* COAR administrative data 2015–2018; MINEDU school census 2014–2017.

TABLE 2 Summary Statistics

	(1) All schools mean/sd	(2) CCT Bandwidth mean/sd
Top applicant is girl	0.57	0.58
	(0.49)	(0.49)
Top applicant is native Spanish speaker	0.87	0.88
	(0.34)	(0.33)
Applicants (#)	2.61	2.60
	(1.61)	(1.56)
Accepted to 2nd round (#)	1.50	1.62
	(0.80)	(0.89)
Enrollment Grade 1 (ln)	3.80	3.83
	(1.06)	(1.10)
Enrollment Grade 2 (ln)	3.76	3.81
	(1.03)	(1.06)
Urban school	0.81	0.83
	(0.39)	(0.38)
Distance to nearest COAR (kms)	71.55	77.06
	(62.00)	(69.58)
District population size (ln)	9.96	9.81
	(1.80)	(1.67)
District poverty rate (%)	42.65	43.10
	(24.07)	(23.82)
Observations	4038	2515

Notes: The table presents means of characteristics of schools that apply to COAR. Column 1 reports statistics for the full sample and Column 2 reports observations within the optimal bandwidth proposed in Calonico et al. (2017). The sample consists of schools applying to COAR for the first time. The population size and the poverty rate are calculated at the district level. *Source:* COAR administrative data 2015–2018; MINEDU school registry and school census 2015–2018; Ministry of Economy and Finance; 2017 Population Census.

TABLE 3 RD Estimates: Balance of Covariates

VARIABLE	(1) RD Estimate
Top applicant is girl	0.00361
	(0.0405)
Top applicant is native Spanish speaker	0.0468*
	(0.0256)
Applicants (#)	0.0913
	(0.114)
Accepted to 2nd Round (#)	0.0825
	(0.0612)
Enrollment Grade 1 (ln)	0.0277
	(0.0862)
Enrollment Grade 2 (ln)	0.0325
	(0.0821)
Urban school	0.00543
	(0.0304)
Distance to nearest COAR (kms)	3.231
	(6.737)
District population size (ln)	-0.0189
	(0.133)
District poverty rate (percent)	-2.182
	(1.961)
Observations in bandwidth	2515

Notes: The table presents the RD estimates of the relationship between the standardized admission rank of the highest-ranking applicants and their characteristics. The sample consists of schools applying to COAR for the first time. The population size and the poverty rate are calculated at the district level. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015-2018, MINEDU school registry and school census 2015–2018; Ministry of Economy and Finance; 2017 Population Census.

TABLE 4 RD Estimates: Effect of COAR Admissions on COAR Applications the Following Year

	(1) At least one applicant	(2) Applicants (#)	(3) Accepted to 2nd round (#)	(4) Admitted (#)
Admitted	0.0436	0.484***	0.300**	0.253***
	(0.0296)	(0.166)	(0.125)	(0.0901)
Observations in bandwidth	2373	2515	2198	2367
Mean D.V. control	0.860	2.449	1.140	0.539
Δ Mean D. V. control	-.1401	.1302	-.3811	.5277

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on school-level applications in year t. The dependent variables by column are: (1) an indicator that at least one student applied to COAR, (2) the number of applicants, (3) the number of applicants accepted to the second round of the admissions process, and (4) the number of applicants admitted to COAR. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019.

TABLE 5 RD Estimates: Effect of COAR Admissions on COAR Applicant Composition and Achievement

	(1) Mean GPA rank	(2) Mean admission score	(3) Max admission score	(4) ECE score
Admitted	-0.154*	0.0526	0.104	-0.484
	(0.0840)	(0.0825)	(0.103)	(7.564)
Observations in bandwidth	2195	2037	2015	1238
Mean D.V. control	-2.029	-0.0434	0.487	626.2

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on applicant composition and achievement in year t. The dependent variables by column are: (1) the mean within-school GPA rank of applicants (multiplied by minus unity, so that a decrease indicates that students have a lower relative GPA within their school), (2) their mean score at the COAR admission exam (standardized with mean 0 and SD 1), (3) the best admission score among them, and (4) their mean score on the ECE held the November before students apply to COAR (standardized with mean 500 and SD 100). ECE scores are a simple average of language and math results. The sample consists of schools applying to COAR for the first time. Column 4 is also restricted to 2016 applicants. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019; ECE 2015.

TABLE 6 RD Estimates: Effect of COAR Admissions on Applications two Years Later

	(1) At least one applicant	(2) Applicants (#)	(3) Accepted to 2nd round (#)	(4) Admitted (#)
Admitted	0.0673***	0.235	0.126	0.104
	(0.0237)	(0.395)	(0.227)	(0.135)
Observations in bandwidth	2254	2039	2003	2043
Mean D.V. control	0.884	5.638	1.752	0.832

Notes: The table presents the regression discontinuity estimates of the effect of COAR admissions in year t-1 on school-level applications in year t+1. The dependent variables presented in each column are: (1) an indicator that at least one student applied to COAR, (2) the number of applicants, (3) the number of applicants accepted to the second round of the admission process, and (4) the number of applicants admitted to COAR. The sample consists schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean D.V. control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015-2019.

TABLE 7 District-Level Analysis RD Estimates: Balance of Covariates

VARIABLE	(1) RD Estimate
Top applicant is girl	0.0940
	(0.0889)
Top applicant is native Spanish speaker	0.0727
	(0.0636)
School applicants (#)	-0.0373
	(0.188)
School accepted to 2nd round (#)	-0.0230
	(0.113)
Urban school	-0.00939
	(0.0609)
Distance to nearest COAR (kms)	9.602
	(12.74)
District population size (ln)	0.196
	(0.208)
District poverty rate (%)	-3.598
	(4.570)
Other district applicants (#)	0.912 *
	(0.539)
Other district applicants accepted to 2nd round (#)	0.303
	(0.223)
Observations in bandwidth	735

Notes: The table presents the RD estimates of the relationship between the standardized admission rank of the highest-ranking applicants and their characteristics at the district level. The sample consists of districts applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2018; MINEDU school registry and school census 2015–2018; Ministry of Economy and Finance; 2017 Population Census.

TABLE 8 District-Level Analysis RD Estimates: Effect of COAR Admissions on COAR Applications the Following Year

	(1) At least one applicant	(2) Applicants (#)	(3) Accepted to 2nd round (#)	(4) Admitted (#)
Admitted	0.00828	1.725	1.170*	0.776**
	(0.0783)	(1.067)	(0.667)	(0.388)
Observations in bandwidth	819	735	760	806
Mean D.V. control	0.551	3.680	1.401	0.521

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on district-level applications in year t. The dependent variables by column are: (1) an indicator that at least one student applied to COAR, (2) the number of applicants, (3) the number of applicants accepted to the second round of the admission process, and (4) the number of applicants admitted to COAR. The sample consists of districts applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019.

TABLE 9 Probability of Applying to COAR in 2016

VARIABLES	(1)	(2)	(3) Females	(4) Males
Female	0.1156***	0.0766***		
	(0.0136)	(0.0080)		
Highly educated mother	0.0801***	0.0745***	0.0888***	0.0645***
	(0.0150)	(0.0097)	(0.0150)	(0.0127)
Native Spanish speaker	-0.0082	0.0150	0.0028	0.0246
	(0.0282)	(0.0142)	(0.0233)	(0.0180)
Urban school		0.0212**	0.0510***	-0.0036
		(0.0107)	(0.0165)	(0.0140)
Distance to closest COAR (kms)		-0.0003***	-0.0004***	-0.0002*
		(0.0001)	(0.0001)	(0.0001)
Enrollment Grade 2 in 2015		-0.0007***	-0.0009***	-0.0006***
		(0.0001)	(0.0001)	(0.0001)
School application to COAR in 2015		0.0679***	0.0811***	0.0590***
		(0.0108)	(0.0163)	(0.0144)
School admission to COAR in 2015		0.0428***	0.0476**	0.0378*
		(0.0142)	(0.0211)	(0.0193)
Observations	12,127	11,946	5,462	6,484
R-squared	0.6431	0.1200	0.1292	0.1074
ECE decile FE	Yes	Yes	Yes	Yes
School FE	Yes	No	No	No
Department FE	No	Yes	Yes	Yes
Department controls	No	Yes	Yes	Yes
Mean D. V.	0.30	0.30	0.34	0.26

Notes: The table presents the ordinary least square estimates of student and school characteristics on the probability of applying to COAR in 2016. The sample consists of grade-2 students for whom we can associate their ECE scores in November 2015 to COAR applications in early 2016 and who are potential COAR applicants (have a GPA above 15 and are among the top three students in their school according to the ECE). Column 1 includes student gender, maternal education (an indicator of secondary school attendance), and mother tongue, controlling for school fixed effects. Column 2 introduces school characteristics. In Columns 3 and 4, the sample is split by gender. All estimations include ECE-decile fixed effects (FE). DV = dependent variables. ***$p<0.01$, **$p<0.5$,*$p<0.1$. *Source:* COAR administrative data 2015–2016; ECE 2015; MINEDU school registry; Ministry of Economy and Finance; 2017 Population Census.

TABLE 10 RD Estimates: Effect of COAR Admissions on COAR Applications the Following Year by Maternal Education

	(1) Applicants with lowly educated mother	(2) Applicants with highly educated mother	(3) Admitted with lowly educated mother	(4) Admitted with highly educated mother
Admitted	0.442***	0.116	0.210***	0.0754
	(0.146)	(0.0883)	(0.0527)	(0.0550)
Observations in bandwidth	2608	2320	2532	2373
Mean D.V. control	1.673	0.563	0.280	0.201

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on school-level applications in year t. The low-education category includes incomplete and complete primary education. The highly educated category includes incomplete and complete secondary education. The dependent variables in the panels are: the number of applicants and the number of applicants admitted to COAR. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019.

TABLE 11 RD Estimates: Effect of COAR Admissions by Gender on COAR Applications the Following Year by Gender

	Top applicant in t-1 female		Top applicant in t-1 is male	
	(1) Female applicants	(2) Male applicants	(3) Female applicants	(4) Male applicants
Admitted	0.0485	0.402***	0.224	0.304*
	(0.173)	(0.127)	(0.183)	(0.164)
Observations in bandwidth	1452	1448	1079	1083
Mean D.V. control	1.790	0.748	1.340	0.967

Notes: The table presents the RD estimates of the effect of COAR admissions by gender of the highest-ranking applicant in the school in year t-1 on school-level applications in year t by gender. The dependent variable in Columns 1 and 3 is the number of female applicants. The dependent variable in Columns 2 and 4 is the number of male applicants. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019.

TABLE 12 RD Estimates: Effect of COAR Admissions on Learning Achievement of Grade-8 Students in Origin Schools

	(1) Median score	(2) Percentile 25
Admitted	0.351	1.259
	(3.221)	(2.780)
Observations in bandwidth	1859	1926
Mean D.V. control	537.4	505.8

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on the learning achievement of grade-8 students who are unlikely to be qualified to apply to COAR. The dependent variables by column are (1) the median and (2) the 25th percentile of the scores on the ECE held the November before students apply to COAR (standardized with mean 500 and SD 100). ECE scores are a simple average of language and math results. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1.
Source: COAR administrative data 2015–2019; ECE 2015.

TABLE 13 RD Estimates: Effect of COAR Admissions on Origin-School Enrollment

	(1) Enrollment-1st grade (ln)	(2) Enrollment-2nd grade (ln)
Admitted	0.0548	0.00202
	(0.114)	(0.115)
Observations in bandwidth	1711	1666
Mean D.V. control	4.034	4.011

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on the enrollment in origin schools in year t. The dependent variables by column are (1) enrollment in first grade and (2) enrollment in second grade. The enrollment in origin schools is expressed in natural logarithms. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019; MINEDU school census 2016–2018.

APPENDIX

I Additional Figures and Tables

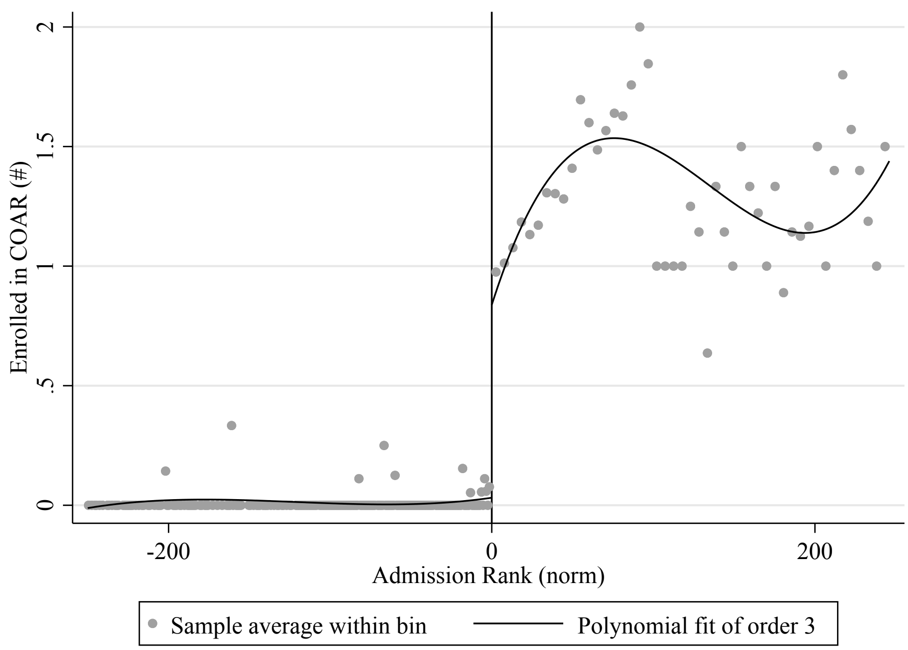


FIGURE A.1 Number of Applicants per School Who Enrolled in COAR by Admission Rank. *Notes:* The figure shows the number of applicants who enrolled in COAR in year t as a function of the standardized admission rank of the highest-ranking applicant in the school in year t-1. The vertical line separates schools with non-admitted (left side) and admitted applicants (right side). The continuous lines represent the second-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2018.

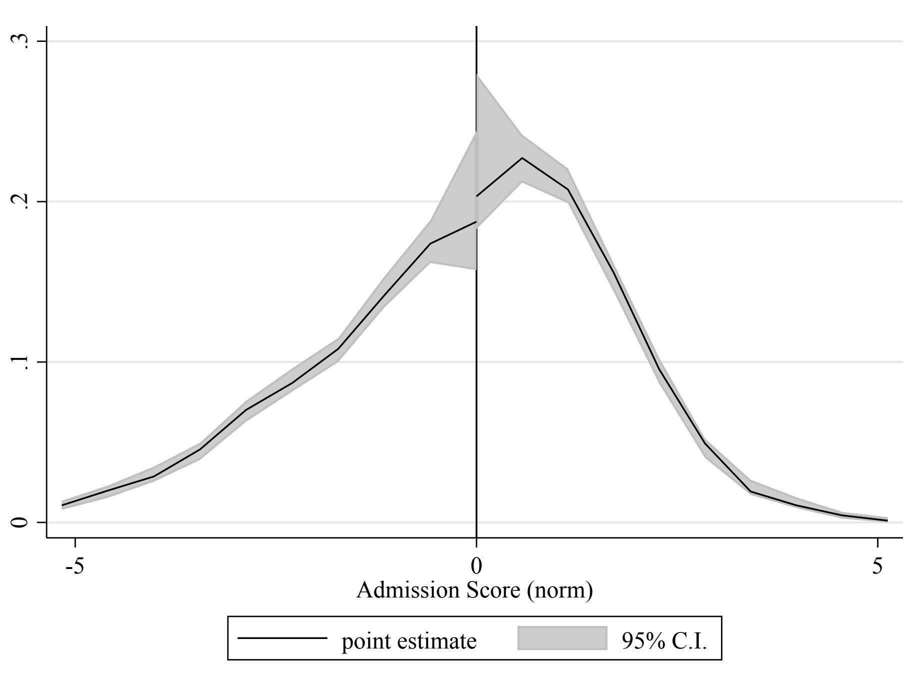


FIGURE A.2 Density of Students by Admission Score.
Notes: The figure plots the density of school-level COAR applicants in year t by the standardized admission rank of the highest-ranking applicant in year t-1. The density is a local polynomial estimator developed by Cattaneo et al. (2018). The vertical line separates non-admitted (left side) and admitted applicants (right side). The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2018.

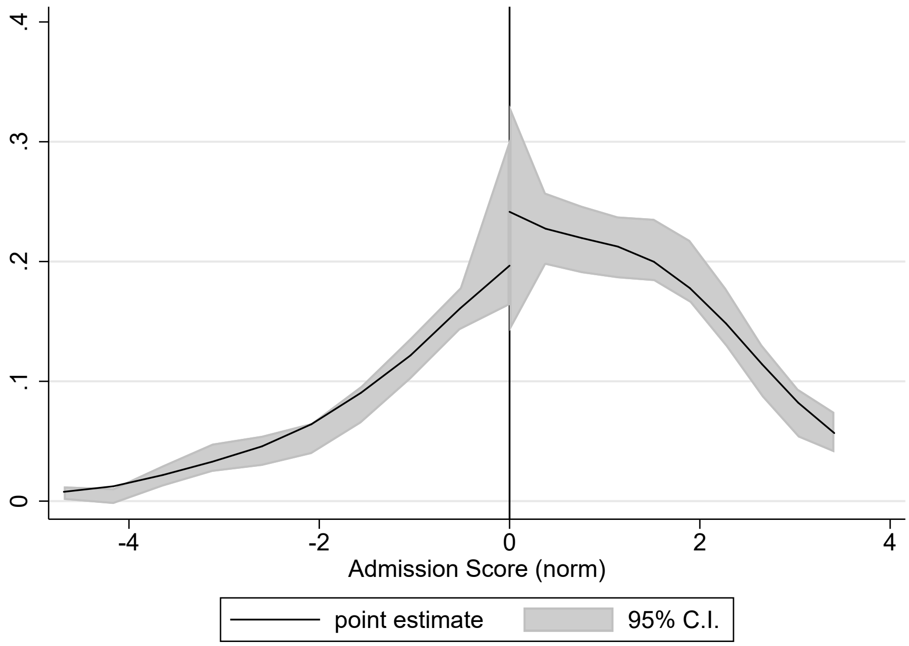
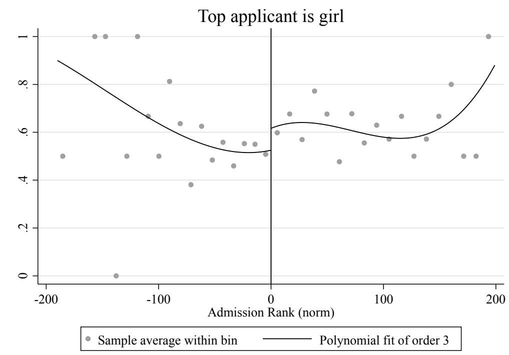
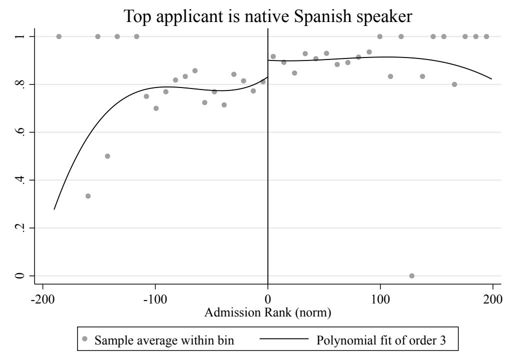


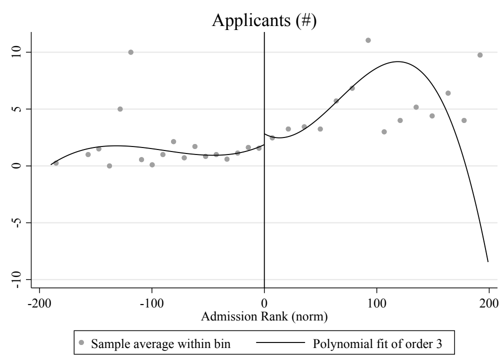
FIGURE A.3 District Level Analysis: Distribution of Students by Admission Score.
Notes: The figure plots the density of district-level COAR applicants in year t by the standardized admission rank of the highest-ranking applicant in year t-1. The density is a local polynomial estimator developed by **?**. The vertical line separates non-admitted (left side) and admitted applicants (right side). The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-96, 98). *Source:* COAR administrative data 2015–2018.



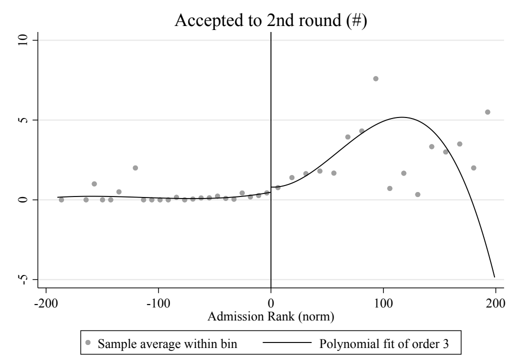
(a) Top applicant is a girl



(b) Top applicant is a native Spanish speaker



(c) Applicants



(d) Applicants Accepted to Second Round

FIGURE A.4 District Level Analysis: Balance of Covariates.
Notes: The figure shows the conditional means of student and school characteristics by the standardized admission rank of the highest-ranking applicant in the district. The bandwidth of the bins used to estimate the local means are computed using the procedure developed by Calonico, Cattaneo and Titiunik (2015) to mimic the underlying variability of the data. The vertical line separates schools with non-admitted (left side) and admitted applicants (right side). The continuous lines represent the third-degree polynomials that best fit the underlying data on each side of the cutoff. The sample consists of schools applying to COAR for the first time. The admission rank is restricted to (-325, 325). *Source:* COAR administrative data 2015–2018; Ministry of Economy and Finance; 2017 Population Census.

TABLE A.1 RD Estimates: Effect of COAR Admissions on COAR Enrollment

	(1) At least one enrolled	(2) Enrolled (#)
Admitted	0.892***	0.894***
	(0.0191)	(0.0331)
Observations in bandwidth	2343	1896
Mean D.V. control	0.0275	0.0372

Notes: The table presents the RD estimates of the effect of COAR admissions on school-level enrollment in COAR . The dependent variables by column are (1) an indicator that at least one student enrolled in COAR and (2) the number of applicants that enrolled in COAR. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019; MINEDU school census 2016–2018.

TABLE A.2 District-Level Analysis: Summary Statistics

	(1) All schools mean/sd	(2) CCT Bandwidth mean/sd
Top applicant is girl	0.57	0.58
	(0.49)	(0.49)
Top applicant is native Spanish speaker	0.83	0.86
	(0.37)	(0.35)
School applicants (#)	2.49	2.45
	(1.36)	(1.28)
School Accepted to 2nd Round (#)	1.59	1.65
	(0.87)	(0.85)
Urban school	0.86	0.87
	(0.35)	(0.34)
Distance to nearest COAR (kms)	88.22	97.33
	(66.11)	(75.58)
District population size (ln)	8.69	8.63
	(1.41)	(1.30)
District poverty rate (%)	50.87	51.08
	(23.88)	(23.28)
Other district applicants (#)	3.23	2.61
	(6.79)	(4.62)
Other district applicants accepted to 2nd Round (#)	1.43	1.16
	(4.06)	(3.08)
Observations	1322	735

Notes: The table presents means of characteristics of the districts that apply to COAR in year t-1. Column 1 reports statistics for the full sample and Column 2 reports observations within the optimal bandwidth proposed in Calonico et al. (2017). The sample consists of districts applying to COAR for the first time. The population size and the poverty rate are calculated at the district level. *Source:* COAR administrative data 2015–2018; MINEDU school registry and school census 2015–2018; Ministry of Economy and Finance; 2017 Population Census.

TABLE A.3 RD Estimates: Effect of COAR Admissions on COAR Applications the Following Year by Gender

	(1) Female applicants	(2) Male applicants	(3) Admitted female	(4) Admitted male
Admitted	0.0802	0.362***	0.0718	0.164***
	(0.134)	(0.0993)	(0.0702)	(0.0540)
Observations in bandwidth	2403	2545	2134	2483
Mean D.V. control	1.636	0.841	0.366	0.187

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on school-level applications in year t. The dependent variables in the panels are: the number of female(male) applicants and the number of female(male) applicants admitted to COAR. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019.

TABLE A.4 RD Estimates: Effect of COAR Admissions on Origin-School Enrollment the Following Year

	(1) Enrollment Grade 1 (ln)	(2) Enrollment Grade 2 (ln)
Admitted	-0.0676	-0.00137
	(0.100)	(0.0980)
Observations in bandwidth	2046	2055
Mean D.V. control	4.024	3.917

Notes: The table presents the RD estimates of the effect of COAR admissions in year t-1 on the enrollment in origin schools in year t+1. The dependent variables are (1) enrollment in first grade and (2) enrollment in second grade. The enrollment in origin schools is expressed in natural logarithms. The sample consists of schools applying to COAR for the first time. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). Mean DV control shows the mean of the dependent variable among non-admitted applicants. ***p<0.01, **p<0.5,*p<0.1. *Source:* COAR administrative data 2015–2019; MINEDU school census 2016–2018.