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JEL Codes: D83, I21, I24.

Keywords: Elite schools, Education inequality, Education externalities,
Information diffusion, Peer effects, School choice.



Learning About Opportunity: Spillovers of Elite School Admissions in Peru^{*}

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Abstract

We study how the admission of a student to an elite secondary school changes the schooling outcomes of younger cohorts in the student's school of origin. The context of the rapid establishment and expansion of a nationwide system of highly selective and free-of-charge secondary schools in Peru allows us to investigate information diffusion with low financial barriers. Using a sharp regression discontinuity design, our analysis shows that the admission of an older schoolmate increases the number of younger students who apply (by 16%) and are admitted (47%) to this elite school system. The effect is concentrated among students whose parents have low education levels. Moreover, admissions of older schoolmates to a selective school gives younger students the opportunity to learn about elite schools, but does not seem to encourage them to improve their learning achievement or provide an advantage in preparing the admission assessments. Our findings show that selective schools can have effects that go beyond their own students and indicate that schoolmates can be an effective channel 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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1 Introduction

Elite schools are a common feature of educational systems across the world. They are often seen as an important policy tool for improving the access of high-achieving, low-income youth to high-quality schooling. However, several studies have documented that talented students from poorer families apply less often to elite schools than those from better-off families, even when schools offer low or no fees, scholarships, or no residence-based restrictions (for example, see [Hastings and Weinstein \(2008\)](#) on the United States, [Ajayi \(2022\)](#) on Ghana, [Guyon and Huillery \(2016\)](#) on France, and [Estrada \(2017\)](#) on Mexico, and reviews in [Pathak and Shi \(2014\)](#); [Pathak \(2017\)](#); [Abdulkadiroğlu et al. \(2018\)](#)).¹ One potential reason behind this difference in demand is that low-income students might not have enough information about the benefits and costs of elite schools, their application processes and admission probabilities, and more generally on whether elite schools are a good match and distinct possibility for them. Lack of information might be more pronounced among youths living in areas and attending schools that have traditionally not sent students to elite institutions, as they might have less access to peers that serve as a source of information and role models.

In this paper, we report the causal effect of an older schoolmate’s admission to an elite school on the application decisions and admission outcomes of younger students. We consider the context of the rapid establishment and expansion of a national system of highly selective secondary schools in Peru named the *Colegios de Alto Rendimiento* (COAR) system. These schools are free of charge which allows the investigation of information diffusion with low financial barriers. To study the information content and possible negative externalities, we examined the effect on the learning outcomes of students who are both eligible and ineligible for application to the elite school.

COAR is a public system of boarding schools that covers the last three grades out of five of secondary education, i.e. ages 15 to 17. This school system started in 2015 with 14 schools and 1,600 students, and reached 25 schools and 2,700 students in 2017. Eligibility requirements are demanding and 28% (16%) of schools did not have a student who met the eligibility criteria in

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

2015 (2019).² Basurto, Zárate and Barron (2020) study 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.

Our identification strategy follows a regression discontinuity (RD) design based on local experiments generated by the centralized admission system. The admission process and the high demand for COAR schools generate an admission cutoff score for each of the 24 administrative departments in which Peru is organized.³ Admission offers increase sharply around these cutoffs creating the local experiments we use. The identification of a causal effect requires that there is no precise manipulation in admission status around the cutoff and we provide evidence on the validity of this assumption (Lee and Lemieux, 2010).⁴ We then compare outcomes of younger students in schools where marginal previous applicants were admitted or rejected.

The dataset we use to implement our identification strategy combines individual data from the COAR application process, the national student registration system, and the national student achievement test. The dataset covers all students who were enrolled in grade 8 in a public school in the 2014–2018 period. This is the population from which potential COAR applicants is drawn. To isolate the effect of a first admission in a school, we restrict the sample to the first year that a school has a marginal student admitted or rejected to COAR and define as our treatment of interest the admission of an originating school's best-performing applicant in the admission assessments.

We find that the admission of an older schoolmate increases the number of students who apply and are admitted to COAR the following year. The admission of (at least) one older schoolmate increases the number of applicants in the school by 0.53, or 17.6% of the mean of 3.04 applicants in schools just below the cutoff. Focusing on eligible applicants, the share of those who apply to COAR increases by 6.1 percentage points, with respect to a mean of 65.8% in the comparison

²Regular secondary schools in Peru offer the five grades of education and hence unsuccessful COAR applicants stay in their original school for the remainder of their studies.

³COAR makes public the number of available seats per school and the list of admitted students to each school. Information on the selectivity of specific schools or on the results of admission assessments is not made public.

⁴The assessment-based admission makes student sorting unlikely. Yet, we look for discontinuities around the cutoff in the density of the running variable (McCrary, 2008) and of 14 baseline characteristics, and did not find any trace of manipulation.

group. The number of admitted students increases by 0.18, or 43% of the mean of 0.4 in schools below the cutoff. The point estimate for the effect on the share of eligible students admitted to COAR is 2.6, with respect to a mean of 12%, but it is not statistically significant.

Regarding mechanisms, we first study whether the admission to COAR of an older schoolmate directly affects the utility that younger students expect to derive from attending a COAR school, by expanding the network that students have in this school system. To investigate this, we estimate an intensive margin effect using the fact that a school can have multiple students admitted to COAR in a given year or over several years. We find no evidence supporting the relevance of this hypothesis.

In contrast, we find evidence on the importance of information by examining the applications from students with less-educated parents, who are less likely to apply to COAR than those with more-educated parents. We only find a significant increase in the applications from students with less-educated parents, by 0.47, or 22% of the mean of the comparison group, which is consistent with the hypothesis that they have less information about COAR. However, we do not observe a corresponding change in admissions. The point estimate for the effect on the number of admissions among students with lowly educated parents is positive (0.06 with respect to a mean of 0.21 in the comparison group), but it is not statistically significant.

We elaborate our examination of the information channel and study the effect on learning achievement (a signal of a change in preferences and effort) and performance on admission assessments. We do not find an effect on any of these outcomes. Hence, the new information that students receive does not seem to translate into higher study effort nor does it seem to be related to how to perform better in the admission assessments.

Even though COAR schools provide free tuition and boarding, children and families living further from COAR schools might face higher costs of attending these schools, such as transportation expenditures. Our results corroborated the role of such costs. Focusing on children of less-educated parents, the effects of previous admissions are high for children enrolled in schools nearer COAR schools, but small and not significantly different from zero for children in schools that are further away from their homes.

Finally, we do not find evidence of a negative externality on the learning achievement of ineligible students, which could occur if school principals and teachers reallocate teaching effort from low- to high-ability students.⁵

Summing up, we find that the admission to COAR of an older schoolmate influences the educational decisions and trajectories of younger students. Our results support the relevance of schoolmates as a source of information for younger students, particularly for those of a disadvantaged background. However, our findings also alert that increasing the demand of high-achieving, low-income youths for elite schools might not be enough to increase access in contexts with highly competitive admissions.

Our paper adds to several literatures. First, we contribute to the literature on the demand for school quality and a related socioeconomic gap (Black, 1999; Bayer et al., 2007; Deming et al., 2014; Chumacero et al., 2011; Boneva and Rauh, 2017; Belfield et al., 2020; Chen and Pereyra, 2019; Kapor et al., 2020).⁶ We contribute to this literature by considering a context of elite schools which are both new and free, which allows the isolation of the critical role of information diffusion on demand. We show how the spillovers of admissions and the diffusion of information through the experience of older schoolmates contribute to narrow the socioeconomic gap in the demand for elite schools.⁷ However we also show that even with minimal direct costs, indirect costs associated with distance (e.g., transportation and security) continue to constrain decisions.⁸

We also contribute to the literature on peer effects in education which has focused on the effects on student achievement, see reviews in Sacerdote (2011) and Sacerdote (2014). A few papers have studied the effect of peers on educational choices. Arcidiacono and Nicholson (2005) and

⁵Bedoya et al. (2019) use a subsample from one cohort in our data and find that the previous 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.

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

⁷A 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, there is no such evidence for lower levels of education.

⁸This result echoes findings from studies on the effect of distance to regular schools on schooling choices. For example, using data from the city of Barcelona, Calsamiglia and Güell (2018) finds that families have a strong preference for schools located closer to their home.

Giorgi et al. (2010) examine the effect of university peers in the choice of medical specialisation and university major choice, respectively. A close literature documentation demand spillovers among siblings. For example, see Dustan (2018) and Dahl et al. (2020) on secondary schools in Mexico and Sweden, respectively, and Altmejd et al. (2021) on tertiary education in Chile, Croatia, Sweden, and the United States. Because these papers focus on spillovers among youth with strong ties (siblings), it is not obvious how their findings translate into the setting of schoolmates or youth without family ties, which matters for policy implications. In contemporary work, Barrios-Fernández (2022) studies the effect of older neighbors on the decision to enroll in university of younger youths who live near. We contribute to this literature in two ways. First by documenting spillover effects among schoolmates at the upper secondary level. Second, and more importantly, our setting allows us to distinguish the effects of first admissions (an extensive margin) and multiple ones (an intensive margin), in contrast to the previous papers which do not differentiate between these two. This is relevant to learning about the relative importance of information diffusion versus the formation of networks in the demand for high-quality education. Third, we examine more closely information diffusion by studying its effects on learning and performance at COAR assessments. Admission to COAR of older schoolmates gives younger students the opportunity to learn about elite schools, but do not seem to encourage them to improve their learning achievement or provide an advantage in preparing the admission assessments. Regarding policy implications, our results contribute to the analysis of interventions to improve the schooling choices of students from disadvantaged backgrounds, by emphasizing the positive externalities of older schoolmates.⁹

Finally, 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 investigating

⁹The 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). The literature on role models suggests that peers can be an outlet to transmit information and shape educational choices, see for example Bettinger and Long (2005); Porter and Serra (2020); Breda et al. (2021) on adult role models and educational choices.

decisions to apply to attend such elite schools, which is key for an understanding of which students will benefit from such applications. Furthermore, we also bring a novel contribution to the field by studying the externalities on the learning achievement of students who are both eligible and ineligible for application to elite schools.

The rest of the paper is organized into the following sections. Section 2 documents the institutional context. Section 3 presents the data and Section 4 describes the research design. Section 5 reports the main results and Section 6 explores the mechanisms. Section 7 concludes.

2 Institutional Context

2.1 The COAR School System

COAR is a public system of boarding schools catered to high-achieving students that covers the last three grades (out of five) of secondary education, while regular schools cover all five years. COAR aims to provide students with high-quality education with a focus on integral development. Consequently, COAR students follow both the national curriculum and an international curriculum (the International Baccalaureate Program) and have access to a strong offering of mentorships and arts, sports, and personal development activities. Students live in dormitories on the premises of COAR schools during the 40 weeks of the academic year and can visit relatives at the weekends. Tuition, boarding, and materials are free of charge, including a laptop, clothing, and books. The Peruvian Ministry of Education (MINEDU, from its Spanish acronym) estimates that the average cost per pupil in COAR is around twice the cost of regular secondary schools.

The COAR system began in 2015 with 14 schools and 1,600 students, and it expanded to 22 schools and 2,400 students in 2016, and to 25 schools and 2,700 students in 2017, when it met its goal of having one COAR school in each of Peru's 24 administrative departments. The capacity of the school system has been stable since then.

Applications to COAR are open to students aged 15 and younger who complete the second

year of secondary education (grade 8) in a public school.¹⁰ COAR eligibility also requires students to have a grade 8 GPA of at least 15 points (on a 20-point scale) and within the top 10 (3 until 2016) of their school.¹¹ This is a high bar. 28% (16%) of schools did not have a student who met the eligibility criteria in 2015 (2019)—see Table A.1 in the online Appendix.

COAR applications soared from 6,330 in 2015 to 30,690 in 2019, due to both the extension of eligibility in 2017 and an increase in applications among eligible students. 67% of eligible students applied to COAR in 2019, up from 42% in 2015. The growing application rates are consistent with a process of information diffusion about COAR among potential applicants, in which they learn about the application procedures, benefits and costs, and suitability of this new school system to their profiles. The larger number of applications translated into increasing selectivity. COAR admitted 9% of applicants in 2019 compared to 25% in 2015. The higher selectivity might discourage some applications, particularly among those who believe that they have low admission chances.¹²

2.2 The Socioeconomic Gap in COAR Applications

COAR aims to provide high-quality education to high-achieving low-income students, weakening the link between socioeconomic status and educational opportunities. Nevertheless, a group of studies have documented the existence of a socioeconomic gap in the demand for elite schools across different contexts, even when the cost of attending such schools is low (for example, see Hastings and Weinstein (2008) on the United States, Ajayi (2022) on Ghana, Guyon and Huillery (2016) on France, and Estrada (2017) on Mexico). We study the socioeconomic gap in COAR applications using data from the COAR application process and the national student registration system for the 2015-2019 period (see details of these datasets in Section 3). As Table 1 reports,

¹⁰Public school students account for 77% of grade 8 enrollment in Peru and tend to be poorer than students enrolled in private schools.

¹¹Students who achieve a top-five position in any national competition organized by MINEDU can also apply to COAR.

¹²As regular schools offer the five grades of secondary education, students who neither apply nor get admitted to COAR can continue their education in the school they attended in grade 8.

64% of eligible students with a highly-educated parent (i.e., with a tertiary education) apply to COAR, a figure that is 13 percentage points lower among those with a lowly educated parent (column 1).¹³ The application gap is of 6 percentage points once we introduce GPA–rank and school fixed effects to control for individual ability and school unobserved characteristics (column 3). Figure A.1 in the online Appendix shows that this gap tends to become smaller after 2015, but remains significant, hence decreasing the socioeconomic gap in the demand for COAR schools. As COAR schools’ applications and attendance are free, this suggests that youths from a disadvantaged background face other binding costs and / or, at least initially, are not sufficiently informed about the benefits of COAR schools. The decreasing gap in demand is consistent with a process of information diffusion, in which we speculate the experience of older peers could play a role.

Table 1: Probability of Applying to COAR

VARIABLES	(1)	(2)	(3)
Lowly educated parent	-0.1290*** (0.0047)	-0.1303*** (0.0047)	-0.0580*** (0.0035)
Female		-0.0045 (0.0031)	-0.0203*** (0.0027)
Observations	148,647	148,647	148,647
R-squared	0.0367	0.0444	0.2998
Cohort FE	Yes	Yes	Yes
GPA rank decile FE	No	Yes	Yes
School FE	No	No	Yes
Mean D.V. lowly educated parent	0.64	0.64	0.64

Notes: The table presents ordinary least square (OLS) estimates of student characteristics on the probability of applying to COAR. The sample consists of students who are eligible for COAR application. Column 1 includes cohort fixed effects; column 2 also includes GPA rank decile fixed effects, and column 3 adds school fixed effects. The table includes the number of observations and the probability of applying for students with lowly educated parent. ***p<0.01, **p<0.5, *p<0.1. *Source:* COAR administrative data 2015–2019; SIAGIE system 2014–2018.

¹³The national student registration system records the education level of the student’s tutor, who in 27% of the cases is the father, on 71% is the mother and on 2% is another relative (or adult).

2.3 Admission Process

COAR admissions are centralized and determined by applicants' performance on admission assessments and their department of residence.

Applications to COAR are open from mid-December to mid-January (the school year runs from March to early December). MINEDU makes public the eligibility requirements, rules of the admission process, and the number of seats available in each COAR school, but not past COAR exam scores or admission cutoffs. Applicants must have the written authorization from their parents or guardians. Students declare two preferred choices of 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 probability of being admitted to the COAR system does not depend on these choices, although the allocation to specific COAR schools does.

In late January, applicants take a standardized test that assesses their literacy and mathematics skills. Applicants with the higher scores (typically the top half) from each department are admitted to a second assessment round in early February. In that second 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%).¹⁴

Applicants are ranked according to their admission score within each department, with those in the first (q_d) positions by department admitted to the COAR system, q_d being a predefined admission quota for each department.¹⁵ Applicants in positions higher than q_d are re-ranked by their admission score in a national list. Those ranked in the first q_n positions on the national list are admitted to the COAR system, q_n being a predefined admission quota. Applicants ranked in positions greater than q_n are placed on a waiting list. A simplified version of this process was in

¹⁴In 2015 and 2016, applicants had to submit a written essay worth 10% of the admission score, and the standardized test was worth 40%.

¹⁵The quotas increased from 2015 to 2017 as more COAR schools opened. The increase was roughly proportional to the initial levels, as one can see in Table A.2 in the online Appendix.

place in 2015, when all admission decisions were made using the department-level rankings (i.e., the sum of the departmental quotas was equal to COAR’s total capacity).¹⁶

Admission results are announced in mid-February. MINEDU publishes the full list of applicants (using their national identification number, not their name) and indicates whether the applicant was admitted to the COAR system and, in that case, the assigned school (admission scores are not published, nor any other information about the selectivity of specific COAR schools). If some applicants decide not to enroll in COAR, an equivalent number of admission offers is made by order of candidates’ rank on the waiting list. However, only a few decline. In the years we analyzed, only 2.4% of the applicants refused an admission offer.

3 Data

3.1 Datasets

The dataset we use for our analysis combines individual data from the COAR application system and the national student registration system (SIAGIE by its Spanish acronym). We used the former to measure past and current COAR applications and admissions (our treatment and outcomes of interest), and the latter to identify potential applicants to COAR and to characterize both potential and actual applicants. We also use micro-data from a national student achievement test (ECE by its Spanish acronym) to study the effect of past COAR admissions on student achievement. The resulting dataset covers all students who pursued grade 8 in a public school between 2014 and 2018. Given the timing of the application process, we refer to students who studied in grade 8 in 2015 (the first cohort treated in our empirical analysis) as the 2016 cohort of potential COAR applicants (and so on). The Peruvian Ministry of Education merged the individual datasets using students’ national identification numbers and provided us with a dataset with an anonymous student

¹⁶Students admitted in the departmental lists are assigned to the COAR school based in their department of residence (or to their first ranked choice if there is no COAR in their department). Students admitted in the national list are assigned to their second ranked choice following their position in that list. If their second choice is full at their assignment time, then MIDENU officials assign them to another school, typically the one closest to their home

identifier and the official school identifier.

COAR administrative records include the applicants' grade 8 school, first and second choice of specific COAR schools, results on each admission assessment, admission outcomes, and enrollment decisions.

The SIAGIE information system includes information on student grades in addition to basic socioeconomic characteristics such as age, gender, native language, and parental education. Schools are obliged to register students in the system at the beginning of the academic year and to report their grades at the end of the academic year. We use this information to estimate the GPA of the students, to characterize their sociodemographic profile and to identify students who are eligible for COAR application thanks to their GPA and age.¹⁷

ECE is a national standardized test administered annually to grade 8 students since 2015. The assessment takes place at the end of the academic year (in November, before COAR applications open) and applies to all schools with at least five students enrolled in grade 8. ECE is a low-stakes exam (does not have an impact on GPA) and measures students' skills in literacy and mathematics. Participation rates are high. 99% (94%) of scheduled schools (students) took the test in 2015.¹⁸ ECE scores are standardized at the national level with a mean of 500 and an SD of 100. For our analysis, we aggregated the literacy and mathematics scores into a composite score taking their mean. In 2017, ECE was canceled due to teacher strikes and meteorological phenomena that shortened the academic year, and therefore we could not study the effect of past COAR admissions on the 2018 cohort of potential applicants' learning achievement.

We complement the resulting data set with information from the 2017 population census on the characteristics of the administrative districts where schools are located.¹⁹ Finally, we obtain the locations of schools from the MINEDU school census and calculate the distance between each origin school and the nearest COAR school.

¹⁷We are not able to identify students who gained COAR eligibility through a MINEDU competition (see Subsection 2.1 for details on COAR eligibility).

¹⁸Coverage increased subsequently and reached more than 99% of targeted schools (and 97% of students) in 2019.

¹⁹Peru is divided into 24 departments and the Constitutional Province of Callao, 196 provinces, and 1,874 districts.

3.2 Samples

Because our identification strategy relies on variation from admitted and rejected marginal students (see details in the next section), we focused our analysis on schools with at least one applicant who reached the second round of the COAR admission process during the 2015-2018 period. We also restrict the analysis to schools with at least five grade 8 students (because that is the cutoff that determines participation in ECE). A total of 3,909 schools fulfill these requirements—38% of all secondary schools with at least five students.²⁰ We have the corresponding SIAGIE records for all these schools, and the corresponding ECE records for 86% of them (excluding 2017). At the individual level, almost all (99.95%) COAR applicants are successfully merged with their SIAGIE record and 98% of grade 8 students to their ECE record.²¹

4 Research Design

4.1 Identification Strategy

We are interested in the causal effect of past COAR admissions on the application decisions and admission outcomes of younger students in a school. For identification, we use the local quasi-random variation around admission cutoffs and compare similar schools with marginally admitted and rejected students. As described in Section 2.3, the admission process generates sharp discontinuities in COAR seat offers around each departmental cutoff. These cutoffs are endogenous to the overall admission process and exogenous from the point of view of any potential applicant. Applicants can influence their admission probabilities through effort (and higher admission scores),

²⁰As one could expect from Table ??, and relevant for external validity, schools in our sample differ from other schools in the characteristics of their students and locations, as they tend to enroll slightly higher numbers of students in grade 8 while being located in less-populated districts and slightly further from COAR schools (see Table A.3 in the online Appendix). However, the characteristics of the best-ranked applicants and socioeconomic compositions do not differ. The question of factors leading some students to apply to COAR first in a school is interesting per se, but not the focus of this paper.

²¹Table A.4 in the online Appendix presents summary statistics for the full sample of schools (column 1) and those within the bandwidth used in our main RD analysis (column 2), using data from the first time in which the school has a second round applicant, which is the one we use in our main results. 43% of the schools appear in the sample for the first time in 2015, 34% in 2016, 10% in 2017, and 13% in 2018.

but the process makes it unlikely that they can precisely manipulate their position around the admission cutoff. This would require them to know ex-ante the full distribution of admission scores within and outside their department and to be able to precisely manipulate their own admission score.

As described in Section 2.3, 50% of the admission score is determined by subjective evaluations in the second round of the admission process. Hence, one potential source of concern is that evaluators might systematically favor some applicants. If evaluators could identify applicants who are on the verge of being admitted, this could lead to the sorting of students with specific characteristics around the admission cutoff, compromising the validity of the RD design. We do not have information to suspect this is an actual practice, but nonetheless we investigate this possibility and, as we show below, find no evidence to support it.

4.2 Admission Cutoffs

We next proceed to define the admission cutoffs we use in our identification strategy. Department d 's cutoff (c_d) is the lowest of two admission scores: the score of the last applicant admitted from the departmental ranking list (s^d , or applicant with ranking q_d) and the score of the last applicant admitted from the national ranking list (s^n , applicant with ranking q_n). To see this, we can distinguish two sets of departments. First, departments with only a few good candidates will only fill the seats reserved at the departmental level, as their candidates cannot compete for seats on the national list, and these departments' cutoffs will equal the one of the departmental list. The marginally admitted applicant in these departments has a ranking q_d and score s^d (where low is $s^d < s^n$). Counter-factually decreasing that student's score until position $q_d + 1$ results in losing admission to COAR, as that score is too low for that applicant to be admitted on the national list. Second, departments with many good candidates will have some candidates admitted in the national list, and the departmental cutoff score will then be the cutoff of the national list. Indeed, in those departments with high s^d cutoffs (i.e., $s^d > s^n$), applicants with ranking q_d , i.e. marginally admitted, would be rejected from COAR only with scores below the national-level cutoff s^n .

4.3 RD estimates

We implement an RD design strategy based on the sharp discontinuities in admission offers that are produced by the COAR admission process. To fix ideas, the reader should first consider the following individual-level model:

$$Applied_{ist} = \alpha + \beta Admitted_{st-1} + \theta score_{st-1} + \delta Admitted_{st-1} \times score_{st-1} + \Gamma X_{ist-1} + \epsilon_{ist} \quad (1)$$

where $Applied_{ist}$ is an indicator variable equal to 1 if student i of school s in year (i.e. cohort) t applies to COAR (we also consider other outcomes), $Admitted_{st-1}$ is an indicator variable equal to 1 if an older schoolmate of student i , in year (cohort) $t - 1$, was admitted to COAR, $score_{st-1}$ is the admission score of that older schoolmate (centered around the departmental cutoff), and X_{ist-1} is a vector of covariates. β is the parameter of interest and captures the effect of the older schoolmate's admission to COAR on the propensity of the younger student to apply his or herself.

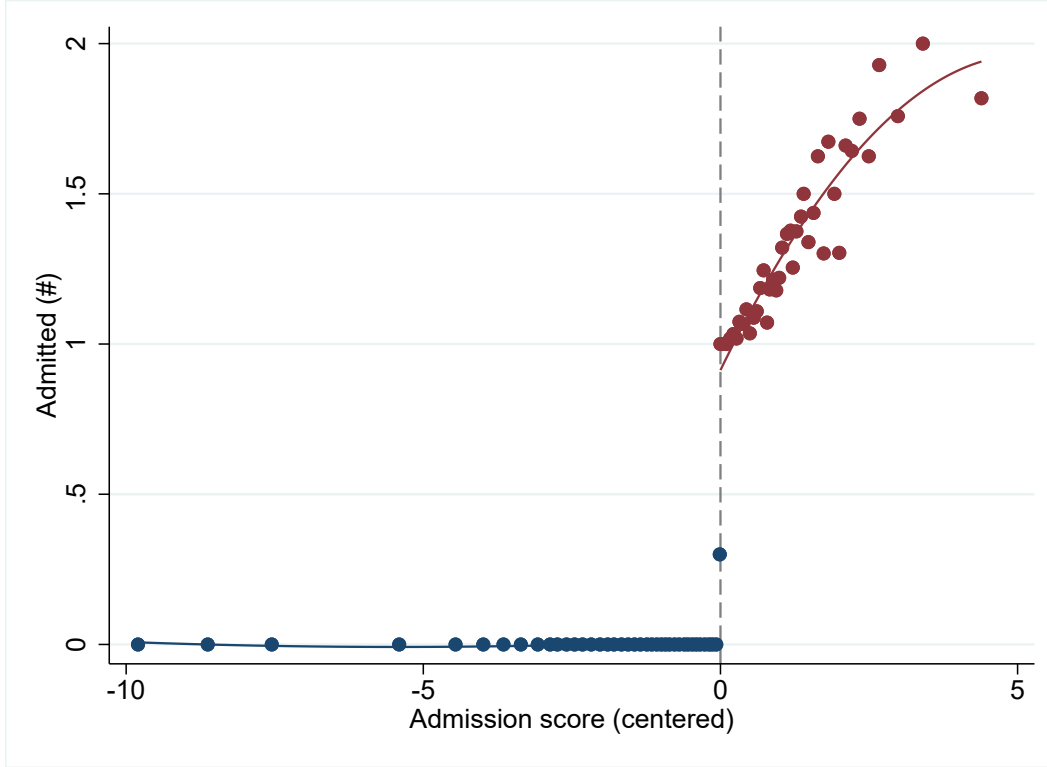
Applications (and admissions) to COAR are not restricted to one student per school. To deal with this multiplicity, we define as our treatment of interest the admission of the student with the highest admission score in the school, and use this score as the running variable. Such definition generates a sharp discontinuity in admission probabilities at the school level, as one can observe in Figure 1.²² In addition, we consider the admission of the second-best applicant in the school, which captures a marginal effect over the admission of the best applicant.²³

The admission of a schoolmate might have an effect on more than one younger student, for example due to multiple direct interactions or to the mediating effect of other students and teachers, and our source of variation in treatment is at the level of the school. Hence, we adopt the following

²²As discussed in Section 2.3, some students decline their admission offer, which leads to the admission of lower ranked applicants. The acceptance rate around the cutoff is very high though (see Figure A.2 in the online Appendix). Therefore, although we report intention-to-treat estimates throughout the paper, they are very close to actual treatment effects.

²³The setting and strategy we use allow us to identify the effect of the admission of specific students, but not the effect of multiple admissions over years or in a given year.

Figure 1: RD Plot: Number of Admitted Students by Admission Score



Notes: The figure shows the number of students admitted to COAR in the year t as a function of the admission score of the school’s best applicant in the admission process in year $t-1$. The vertical lines separate schools with non-admitted (left side) and admitted (right side) applicants in the 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 with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015–2018 period. *Source:* COAR administrative data 2015–2018.

school-level model:

$$Applicants_{st} = \alpha + \beta Admitted_{st-1} + \theta score_{st-1} + \delta Admitted_{st-1} \times score_{st-1} + \Gamma X_{st-1} + \epsilon_{st} \quad (2)$$

where $Applicants_{st}$ is the number of COAR applicants in school s and year t and the variables on the right side remain unchanged. We also use the share of eligible students in the school who apply to COAR ($Share_{st}$) as an outcome. This share captures the individual propensity to apply among eligible students. However, it leaves out applications from students that we cannot identify as eligible (see Section 3.1). In addition, the number of eligible students is potentially endogenous,

varies between schools, which makes interpretation harder, and may be zero in some schools, which reduces sample size. Therefore, the number of applicants at the school-level ($Applicants_{st}$) is our preferred outcome.

Finally, the situation in which the older student was also exposed to admission to the same elite school of an even older schoolmate should be considered. This second older schoolmate could recursively have been exposed to the admission experiences of older schoolmates. This is possible in contexts where the elite school in question has been in operation for a long time. β would then capture the marginal effect of the older student’s admission over the history of past admissions in school s , i.e. an intensive margin effect. One advantage of our context is that COAR is of recent creation. We could thus restrict the sample to the first time a student from a given school is admitted to COAR and isolate the effect of the first admission, i.e., an extensive margin effect. We follow this approach in our main analysis, although we also report results without this restriction.

We estimate equation 2 in a sample of schools close to the admission cutoff, which we obtain using the optimal bandwidth algorithm developed by Calonico, Cattaneo and Farrell (2019a). Given that the admission cutoff scores vary over years and for departments that do not send applicants on the national list, our estimates aggregate a number of local experiments and we stack observations for different departments and cohorts. To account for this, we introduce admission cutoff fixed effects. To improve efficiency, we include a set of baseline covariates (the same as those listed in Table A.4). We added the covariates to the regression in an additive-separable, linear-in-parameters way, as suggested in Calonico et al. (2019b).²⁴ We then report bias-corrected RD estimates and standard errors as proposed in Calonico, Cattaneo and Farrell (2019a), Calonico, Cattaneo and Farrell (2018), and Calonico, Cattaneo and Titiunik (2014).

When estimating equation 2, we use the score as the running variable in our preferred specification, but also estimate an alternative specification using the applicant’s rank in the admission queue (i.e. the variable that finally determines admission). The rank is a deterministic function of the score, and hence one expects both specifications to produce similar results. However, the

²⁴Results are robust to the exclusion of these covariates, as we show below.

transformation of scores into ranks discards cardinal information on relative positions from the cutoffs, hence modifying the weights allocated to different observations around the cutoffs and the estimates obtained. The score will preserve this information.

We verify the validity of the identification assumption (that there is no precise manipulation of treatment status close to the cutoff) by looking first at the density of the running variable, the older student's admission score, around the cutoff to detect a discontinuity that would indicate the existence of manipulation (McCrary, 2008). We do not find evidence of this discontinuity, the point estimate is -0.6114 and the associated p-value is 0.5409, see Figure A.3 in the online Appendix. Furthermore, we check for imbalances around the admission cutoff of 14 baseline characteristics, another signal of manipulation. Table 2 reports the corresponding RD estimates. Overall, they have a small magnitude and none is statistically significant (see the corresponding RD plots in Figures A.4 and A.5 in the online Appendix). Hence, we do not find any trace of manipulation, which supports the causal interpretation of the RD estimates.

5 Main Results

Figure 2 shows the relationship between COAR applications of younger students and the COAR admission score of their schoolmate from the previous cohort with the best performance in the assessments. As shown in panels A and B, applications of younger students increase discontinuously and markedly when marginal older schoolmates are admitted, and, as seen in panels C and D, their admission outcomes then also increase discontinuously but to a lesser extent. Panel A in Table 3 reports the corresponding regression estimates. As seen in column 1, we find no statistically significant effect on the probability that at least one student in the school applies to COAR but the point estimate is positive at 4.6 percentage points (and this probability is already high, at 85%, in schools just below the cutoff). However, the number of applicants increases by 0.53, or 17% of the mean of 3.04 applicants in schools below the cutoff (column 2). The number of applicants accepted to the second round increases by 0.18, or 19% of the mean of 0.93 (column 3), and the

Table 2: Balance of Covariates

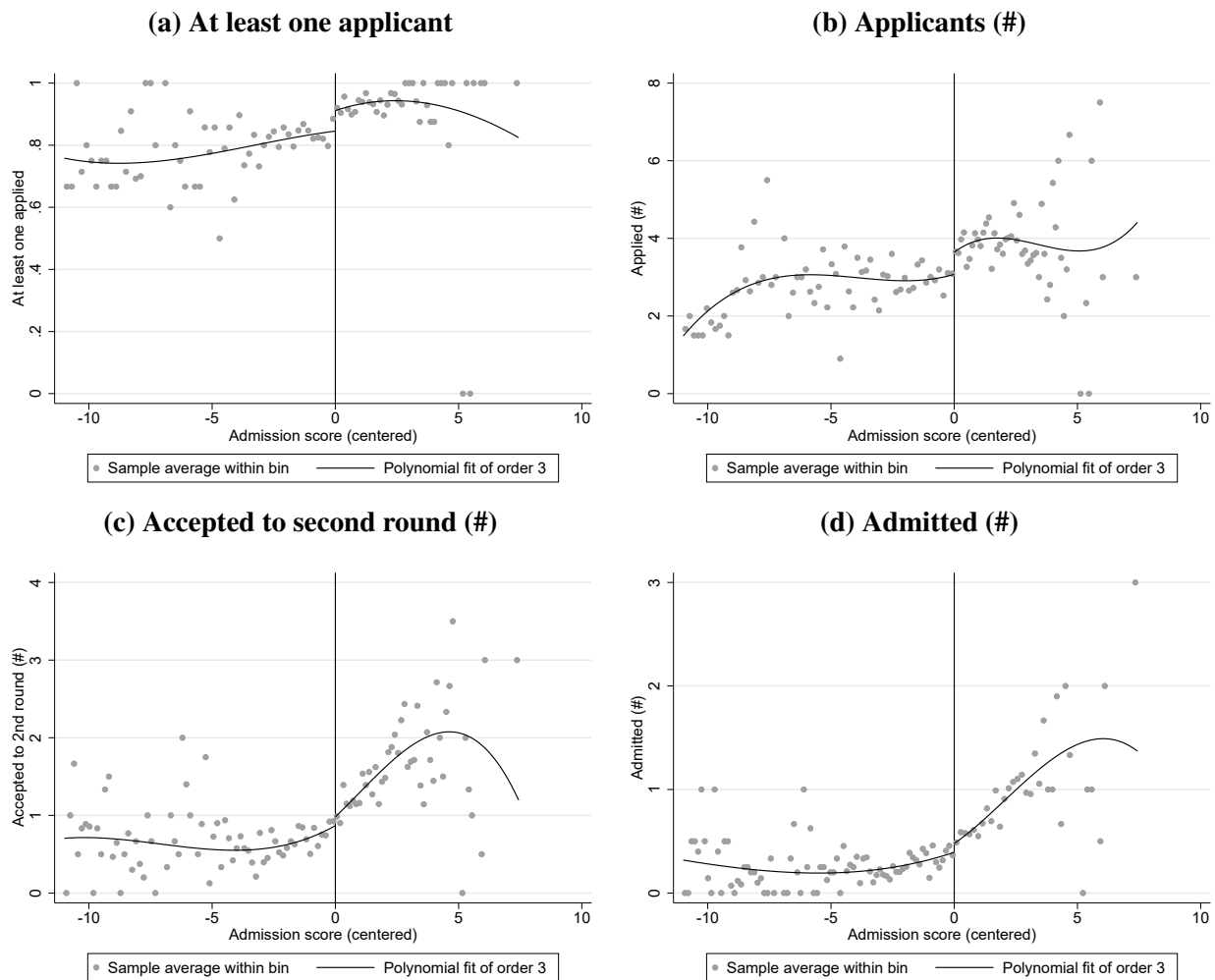
Variables	(1) RD Estimate
Female	-0.0366 (0.0515)
Mother tongue is Spanish	-0.0103 (0.0336)
Lowly-educated parent	-0.00245 (0.0492)
Grade 8 GPA	-0.0184 (0.0591)
Grade 8 students (#)	-2.526 (7.102)
Female students (share)	0.00361 (0.0159)
Native Spanish speakers (share)	-0.00580 (0.0311)
Students with lowly educated parents (share)	-0.00333 (0.00955)
Eligible students (share)	0.00724 (0.00885)
Applicants (#)	0.0954 (0.144)
Urban school	0.00263 (0.0395)
Distance to nearest COAR (kms)	-1.705 (5.127)
District population size (thousands)	3.786 (14.90)
District poverty rate (%)	0.644 (2.147)
Observations in bandwidth	2249

Notes: The table presents the RD estimates of balance checks for 14 baseline covariates. The estimates were obtained from a local linear regression using the optimal bandwidth based on [Calonico et al. \(2017\)](#). The sample consisted of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: COAR administrative data 2015-2018; SIAGIE system 2014–2017; 2017 Population Census.

number of admitted students by 0.18, or 43% of the mean of 0.40 (column 4). Panel B of the same table shows that the admission of an older schoolmate increases the share of eligible students in the school who apply to COAR by 6.1 percentage points, or 9.3% of the mean of 66 percent in schools below the cutoff (column 1), and the share who is accepted to the second round by 4.6 percentage points, or 19% of the mean of 24% (columns 2). The share of eligible students admitted to COAR also increases, by 2.6 percentage points or 22% of the mean of 12% according to

the point estimate, but this increase is not statistically significant (the p-value is 0.16). We do not observe that past admissions significantly affect the number of eligible students among the younger cohort. Regressing this variable as an outcome produces a point estimate of 0.32 with a p-value of 0.21. Hence, the admission to COAR of an older schoolmate significantly increases the number of COAR applications, and possibly also (with weaker evidence) admissions of younger students the next year in the same school.

Figure 2: COAR Applications by Admission Score



Notes: The figure shows the conditional means of school-level applications to COAR in year t as a function of the admission score of the best applicant in the school in year $t-1$. Observations are grouped into bins based on [Calonico et al. \(2017\)](#). The vertical lines indicate the admission cutoff 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 with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. *Source:* COAR administrative data 2015-2019.

Table 3: Effect of Older Schoolmate on COAR Applications

	(1) At least one applied	(2) Applied	(3) Accepted to 2nd round	(4) Admitted
Panel A. Number of students				
Older schoolmate is admitted	0.0462 (0.0310)	0.527** (0.243)	0.178* (0.106)	0.176** (0.0811)
Observations in bandwidth	2084	2030	2026	2260
Mean D.V. control	0.852	3.039	0.935	0.404
Panel B. Share of eligible students				
Older schoolmate is admitted		0.0611* (0.0351)	0.0461* (0.0266)	0.0258 (0.0183)
Observations in bandwidth		1823	2172	2634
Mean D.V. control		0.658	0.244	0.116

Notes: The table presents the RD estimates of the effect of an older schoolmate's admission to COAR on school-level applications the following year (see equation 2). The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. The number of observations and the estimated mean of the dependent variable at the left of the admission cutoff are reported at the end of each panel. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015-2019.

For robustness checks, panel A of Table A.5 in the online appendix reproduces the main results, but without the baseline covariates. The findings are consistent with those reported in Table 3. Although our treatment is at the level of the school, some schools are geographically close by, which can make it easier for students (and teachers) of these different schools to interact with each other and make place for spatial externalities. As shown in panel B of Table A.5, the results are robust, allowing for such spatial externalities by clustering the standard errors at the level of the administrative district (the smallest administrative unit in Peru). Finally, we use the admission rank as the running variable and replicate the main specification. As reported in panel C of Table A.5, point estimates are larger and the estimated effects have higher statistical significance (all are significant at the one percent level) than in our preferred specification using the admission score as the running variable.

As described in Section 2, the COAR system became more selective over time, with a steep increase in 2017 (10% of applicants were admitted in that year vs. 23% in 2016). Although

higher selectivity and application rates could limit the effect of schoolmates on new applications and admissions, we do not find evidence of such a decline when estimating effects for different application cohorts (see Figure [A.6](#) in the online Appendix). Because the sample of schools with first marginal applications is smaller and reducing over time, point estimates are noisy for later cohorts, but the magnitude of the estimated effects increases if anything, except for a decrease for the 2017 cohort which corresponds to the surge in applications that year.

6 Mechanisms

The results presented in the previous section show that previous COAR admissions in a school significantly affect the educational choices and COAR admissions of younger students. We now focus on the mechanisms behind these spillovers.

6.1 Direct Utility

The admission to COAR of a schoolmate could directly affect the utility that younger students expect to derive from attending a COAR school, by expanding the network that students have in this school system. Table [4](#) reports the estimated effects of the marginal admission of a second-best older applicant in the school (still using equation [2](#) but now with the admission score of that second-best applicant as the running variable) and the estimated effects of a second marginal admission in schools that already had an application in a previous year. Both of those factors capture intensive margin effects, i.e. the effect of having an additional admission (compared to only one) in the same year and the effect of an additional admission given a past history of applications (compared to the first time of application). While estimated for subsets of the sample and hence not directly comparable to the main parameters of interest, we would expect these admissions to have significant effects if the formation of networks drove the higher demand of younger students. The point estimate for the effect of the admission of the second-best applicant is 0.41 (column 1) while the one for second-time marginal admissions is 0.12 (column 3). But neither of those is statistically

significant, nor are the coefficients for the corresponding estimated effects on admissions (columns 2 and 4). Hence, although the samples are smaller here and estimates noisier, we did not find evidence supporting a direct utility channel, whereby every marginal admission would matter.

Table 4: Effect of Older Schoolmate on COAR Applications: Admission of Second Best Applicant and Second Time of Application

	Admission of 2nd best applicant		2nd-time of application	
	(1) Applied	(2) Admitted	(3) Applied	(4) Admitted
Older peer is admitted	0.414 (0.336)	-0.0180 (0.156)	0.125 (0.375)	-0.152 (0.138)
Observations in bandwidth	849	678	1531	1036
Mean D.V. control	4.250	0.763	6.506	0.703

Notes: The table presents the RD estimates of the effect of an older schoolmate’s admission to COAR on school-level applications the following year (see equation 2). The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. The number of observations and the estimated mean of the dependent variable at the left of the admission cutoff are reported at the end of each panel. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015-2019.

6.2 Information

The admission to the COAR of a schoolmate can give younger students the opportunity to learn about COAR schools, their benefits and costs, the admission process, and whether this elite school system is a good match for them. As described in Section 2, while it decreases over time, there is a socioeconomic gap in the demand for COAR schools, even within schools. This suggests that youths from disadvantaged backgrounds might have lower access to information about elite schools, likely because their parents and others in their social environment lack the education or network that matter in learning about these new opportunities. These youths could then potentially benefit more from the COAR admission of schoolmates. To investigate this channel, Table 5 presents heterogeneity results by parental education. While marginal failures to gain admission could also provide useful information, we capture here the additional information benefits that full COAR admissions and experiences of older schoolmates provide. We find that the admission

to COAR of an older schoolmate increases the number of applications of students with poorly educated parents by 0.47 (or 22% with respect to a mean of 2.12 in schools just below the admission cutoff). In contrast, the estimated effect on students with highly educated parents is small (0.05) and not statistically significant. This evidence supports such an information diffusion benefiting specifically disadvantaged youths.

Nevertheless, we do not observe that changes in applications closely follow those of admissions. The point estimate for the effect on the number of admissions among students with poorly educated parents is small (0.06 with respect to a mean of 0.21 in schools in the comparison group) and not significant, while the number of admissions among students with highly educated parents admission increases more, by 0.12 (with respect to a mean of 0.17 in the comparison group). This suggests that even among students who are eligible for COAR application and induced to apply, disadvantaged youths perform less well than more advantaged ones at the COAR assessments (see more below).²⁵

6.3 Preferences and Learning about COAR schools

Admissions of older schoolmates might bring different sorts of information at different times in the school year. Information stemming from previous admissions concerning the benefits and returns from COAR education could arrive early in the school year, modify educational plans of potential applicants and induce them to increase their study effort. Information on the existence of COAR schooling opportunities could also come or become salient later in the year, in particular during the period of COAR applications. In that later case, spillovers might not affect students' learning effort, but mostly induce them to apply or maybe help them prepare for the COAR exam.

²⁵Information might flow more easily among student who share similar characteristics, either because they might be more likely to interact with each other or because younger students might consider the experience of older students who are more similar to them as more informative. We examine in Table A.6 whether the identified spillovers vary by the sociodemographic similarity (proxied by parental education) of older and younger schoolmates. The estimates are noisy and provide mixed results. Students with poorly educated parents increase their applications whatever the older student's parental education (although the results are only significant when the older student has a highly educated parent). The estimates are not statistically significant for students with highly educated parents (although the point estimates are positive for the effects of previous admissions of older schoolmates with a similar advantaged background (point estimate is 0.15).

Table 5: Effect of Older Schoolmate on COAR Applications by Parental Education

	Lowly-educated parent		Highly-educated parent	
	Applied	Admitted	Applied	Admitted
Older schoolmate is admitted	0.466** (0.223)	0.0623 (0.0537)	0.0548 (0.0938)	0.121** (0.0506)
Observations in bandwidth	1928	2561	2172	2088
Mean D.V. control	2.126	0.209	0.658	0.167

Notes: The table presents the RD estimates of the effect of an older schoolmate’s admission to COAR on school-level applications the following year by parental education (see equation 2). The highly-educated category includes tertiary education or more. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. The number of observations and the estimated mean of the dependent variable at the left of the admission cutoff are reported at the end of each panel. ***p<0.01, **p<0.05, *p<0.1. *Source:* COAR administrative data 2015-2019.

To investigate this, Table 6 reports the effects of previous COAR admissions on the learning achievement of grade 8 students measured by their GPA and scores on the ECE national test. In the first two columns, we estimate spillovers on achievement for students who are eligible for COAR application and find that neither their GPA nor their ECE scores are affected.²⁶ Hence, admissions to COAR of older schoolmates induce eligible students to apply to such schools, but apparently do not encourage them to improve their achievement at least not during the school year. We discuss the estimates in the last two columns of Table 6 below.

Another piece of evidence on changes in learning achievement is provided by the COAR admission assessments. Table 7 reports results on the effect of the admission of an older schoolmate on the performance of younger applicants in COAR admission assessments. These estimates are informative concerning the group of individuals who decided to apply to COAR (and took the admission test, column 1) and, among them, those who reached the second round of the admission process (thus participating in the admission interview and social activities, column 2). Besides increasing their study effort, younger students who decide to apply to COAR could perform better with past admissions also because they learn about the mechanics of the assessments. The results

²⁶ECE was canceled in 2017 and hence the results reported in Table 6 exclude the 2018 cohort. We show in Table A.7 in the online Appendix that the main results on applications are robust to this sample exclusion. The coefficients for admissions have a similar magnitude to those reported in Table 3, but are not statistically significant.

Table 6: Effect of Older Schoolmate on Learning Achievement

	Eligible students		Non-eligible students	
	(1) GPA	(2) ECE score	(3) GPA	(4) ECE score
Older schoolmate is admitted	0.0441 (0.0986)	-4.382 (4.679)	-0.0256 (0.0671)	-1.382 (2.464)
Observations in bandwidth	2235	1886	2372	1854
Mean D.V. control	16.39	614.3	12.51	535.8

Notes: The table presents the RD estimates of the effect of an older schoolmate’s admission to COAR on the learning achievement of grade 8 students measured by their GPA and scores in the ECE national test. ECE scores are a simple average of literacy and mathematics results. The estimates are obtained from a local linear regression using the optimal bandwidth based on [Calonico et al. \(2017\)](#). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. It is split into eligible and non-eligible students for COAR application. ECE was canceled in 2017 and hence columns (2) and (4) exclude the 2018 cohort. The number of observations and the mean of the dependent variable among non-admitted applicants are reported below each coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015–2019; SIAGIE system 2014-2018; ECE 2015, 2016 and 2018.

in Table [7](#) show no more effects on the COAR admission scores than on the GPA and ECE tests. These results confirm that potential applicants are not increasing their study effort. While selection effects with the higher number of applicants could play in the opposite direction, they also suggest that past admissions do not provide a decisive advantage in preparing the COAR exam. Neither we find effects on the admission test scores if we divide students by their parental education. The coefficient for the effect among the youths with lowly educated parents is -0.004 and for the youths with highly educated parents is 0.14, but both are statistically insignificant, see Table [A.8](#) in the online appendix. It stands out though that students with more educated parents tend to perform better in the admission test. Students from this group in the control schools have an average score of 0.2 SD in the admission test, while those with less educated parents have an average score of -0.03 SD (which helps to explain the heterogeneous effects in admissions discussed in the previous section).

Table 7: Effect of Older Schoolmate on COAR Admission Scores

	(1) Standardized test	(2) Subjective evaluations
Older schoolmate is admitted	0.0798 (0.0671)	0.0765 (0.0895)
Observations in bandwidth	1895	1329
Mean D.V. control	-0.0340	0.0480

Notes: The table presents the RD estimates of the effect of an older schoolmate’s admission to COAR on the performance of younger applicants in the COAR admission assessments. The dependent variables are: (1) the standardized mean score in the COAR admission test, and (2) the standardized socioemotional assessment score for those applicants who reached the second round of the admission process. This score is a compound of the assessment during the admission interview and social activities. The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. The number of observations and the mean of the dependent variable among non-admitted applicants are reported below each coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015-2019.

6.4 Externalities on the Non-eligible

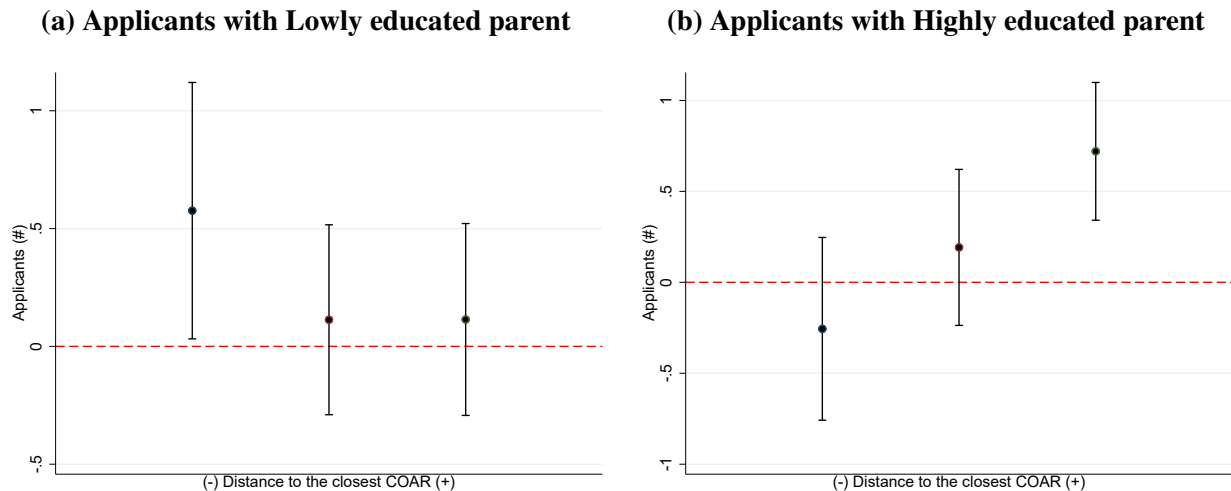
The admission of students to COAR could motivate changes in the learning conditions in the origin schools that affect students who are both eligible and non-eligible to apply to COAR. If teachers (or principals) reallocate inputs to potential COAR applicants, past admissions could generate negative externalities on learning by the other students in the school. The lack of effects on the learning of the eligible youths suggests that this does not occur. However, we directly investigate the existence of negative externalities on the non-eligible students. The last two columns of Table 6 report the effects on ECE test scores of students who are not eligible to apply to COAR and show there is no evidence of negative effects on their learning achievement.

6.5 Cost of Distance

While COAR schooling and boarding are free, applications to COAR should still depend on some remaining costs of attendance, notably transportation. A COAR school’s location relative to a student’s home is a primary factor of these attendance costs, as children and families who live far

from COAR schools face higher transportation costs (and maybe psychological or other costs of attending a school further away from home). We thus investigate possible heterogeneous effects of past admissions according to both parental education and distance to the closest COAR school. When comparing these estimates, one should be careful since the groups are likely to differ for other associated dimensions, like the characteristics of schools. Figure 3 reports the RD estimates for the number of COAR applications by parental 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 parents and enrolled in schools near COAR schools and for children with more educated parents and enrolled in schools far away. This suggests that even in a setting with free tuition and boarding, relatively small remaining costs influence decisions to apply to COAR schools.

Figure 3: Effect of Older Schoolmate on COAR Applications by Parental Education and Distance to COAR



Notes: The figures show the heterogeneity effect of an older schoolmate’s admission to COAR on the number of students that applied to COAR the following year with highly educated and low-educated parents by distance to the nearest COAR school. The distance in kilometers between the origin school of the older peer and the nearest COAR school is calculated regardless to what department the school belongs. The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015–2018 period. It is split into terciles of the distance to the nearest COAR school from students’ 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. \(2017\)](#). *Source:* COAR administrative data 2015–2019; SIAGIE system 2014-2018.

7 Conclusions

The evidence presented in this paper shows that the admission of an older schoolmate to COAR increases the number of younger students who apply (by 17%) to this elite school system. The effect is concentrated among students from less-educated families, who are more likely to lack information about elite schools. This suggests that admissions from older schoolmates . This is good news for the aim of reducing education inequality. However, higher application rates do not necessarily translate into higher admission rates. Even among the selected group of students who are eligible for COAR application, applicants with poorly educated parents tend to under-perform in the admission assessments compared to applicants with highly educated parents. Moreover admissions to COAR of older schoolmates, while giving them the opportunity to learn about elite schools, apparently do not seem to encourage younger students to improve their learning achievement or provide an advantage in preparing the admission exam. The results also show that the costs associated with distance to COAR schools constrain application decisions. In particular, the effects of previous admissions on youths with poorly educated parents are only significant among those who reside close to COAR schools.

A rich literature in economics and sociology has documented that high-achieving, low-income youths tend to have a lower demand for elite schools. The results presented here show that the diffusion of information is a key factor for increasing the demand for elite education of children from disadvantaged backgrounds. Some barriers to exam preparation might constrain admissions of these children to COAR schools and this needs to be addressed with complementary policy interventions. But the experience of schoolmates can make a difference and, hence, the use of positive discrimination policies in admission decisions could have important demand spillovers.

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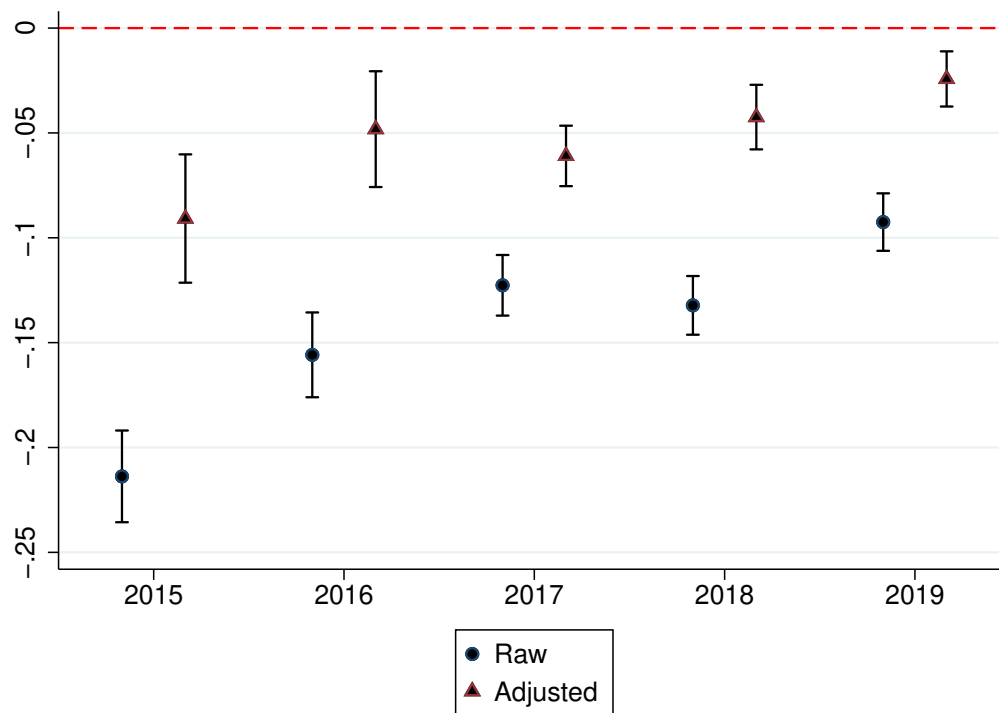
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Online Appendix

A. Additional Figures and Tables

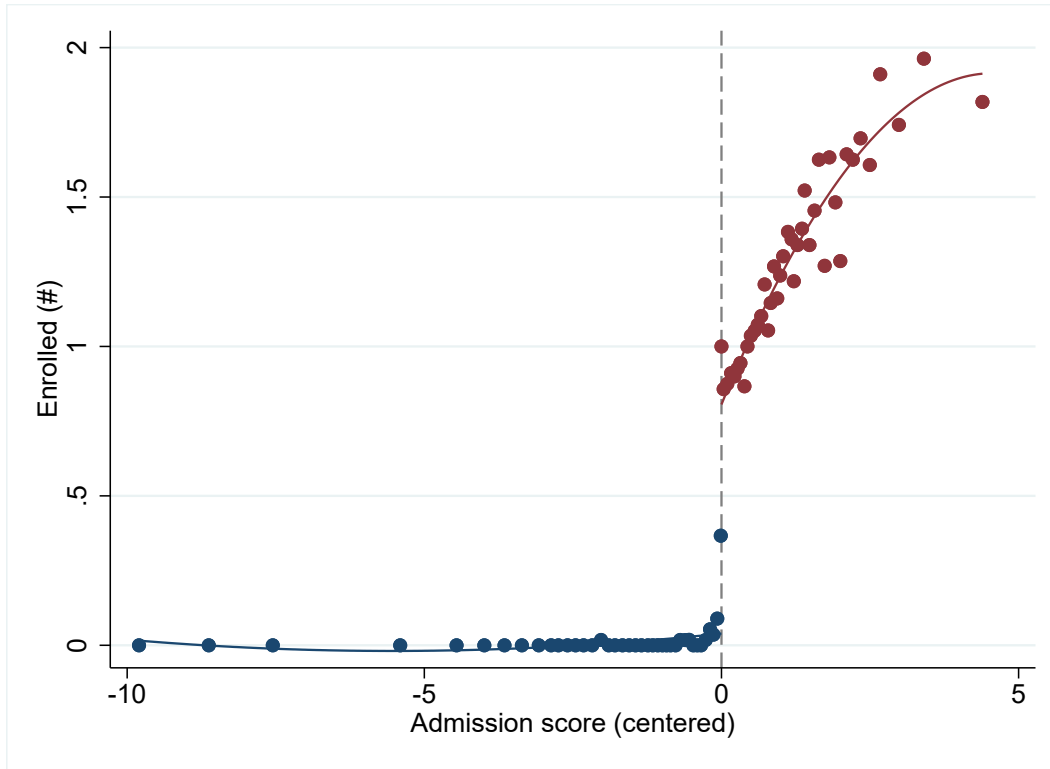
Figures

Figure A.1: OLS Estimates: Socioeconomic Gap in COAR Applications by Year



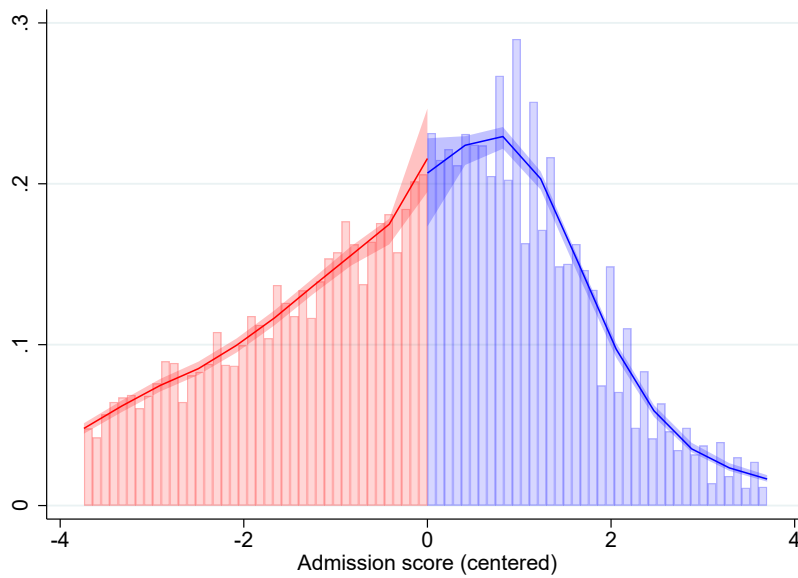
Notes: The figure presents ordinary least square (OLS) estimates of the socioeconomic gap in COAR application by year in the 2015-2019 period. The figure plots the point estimates and 95% confidence intervals of models (1) (raw with controlling only for cohort fixed effects) and (3) (adjusted controlling for GPA rank decile fixed effects and school fixed effects) from Table [1](#). The sample consists of students who are eligible for COAR application. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015–2019; SIAGIE system 2014–2018.

Figure A.2: Number of Students Enrolled in COAR by Admission Score



Notes: The figure shows the number of students enrolled to COAR in year t as a function of the centered admission score of the school's best applicant in the admission process in year $t-1$. The vertical line separates schools with nonadmitted (left side) and admitted (right side) applicants 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 with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. *Source:* COAR administrative data 2015–2019.

Figure A.3: Density of COAR Admission Score



Notes: The figure plots the density of COAR admission scores (centered). The density is a local polynomial estimator developed by Cattaneo et al. (2018). The vertical line separates non-admitted (left side) and admitted (right side) applicants. *Source:* COAR administrative data 2015–2019.

Figure A.4: Balance of Covariates: Applicant Characteristics by Admission Score

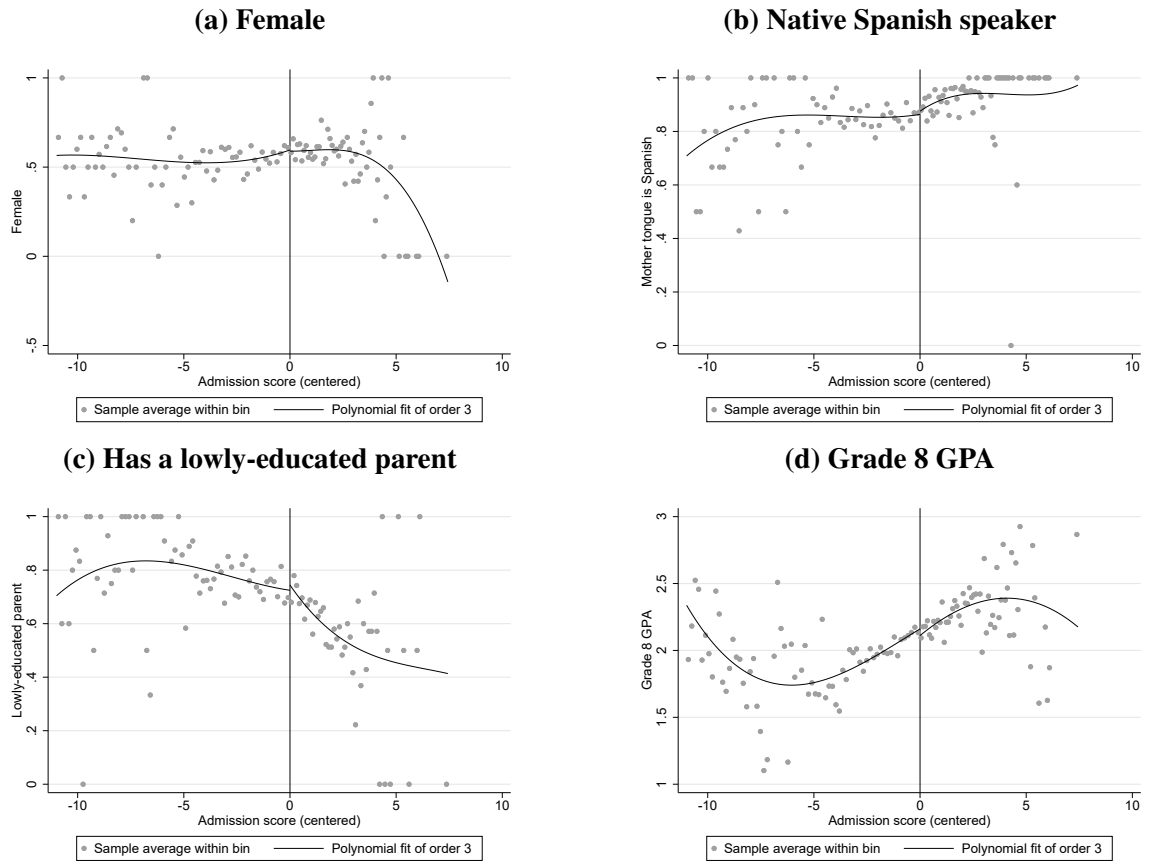
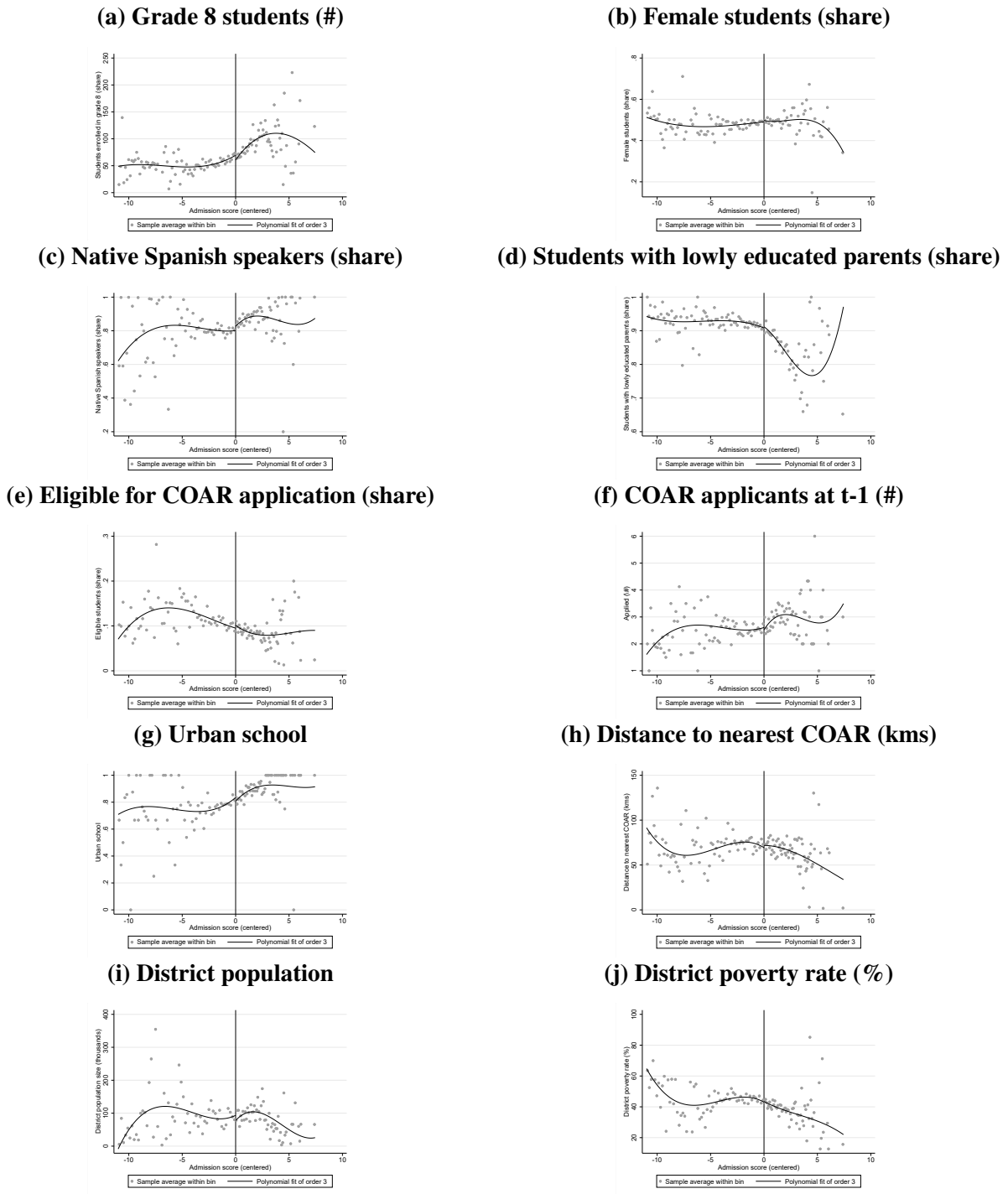
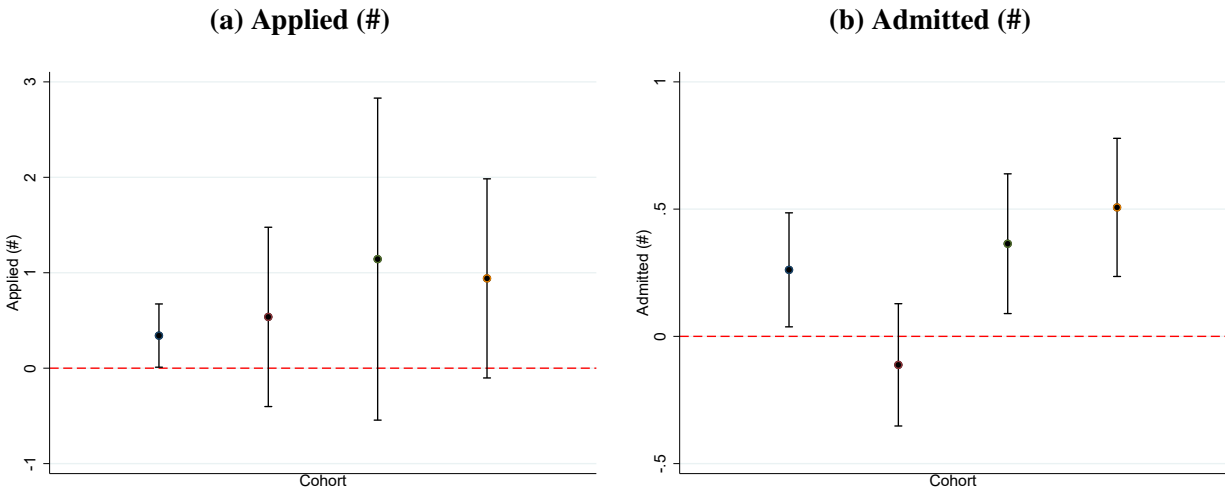


Figure A.5: Balance of Covariates: School characteristics by Admission Score



Notes: The figure shows the conditional means of school characteristics by the admission score of the best 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 (right side) applicants 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 with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015–2018 period. *Source:* COAR administrative data, SIAGIE system, and 2017 Population Census.

Figure A.6: RD Estimates: Effect of Older Schoolmate on COAR Applications by Cohort



Notes: The figures show the effect of an older schoolmate’s admission to COAR on the number of students that applied to COAR the following year by application cohort. The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015–2018 period. The figures plot the corresponding point estimates and 90% confidence intervals. All estimates correspond to local linear regressions using the optimal bandwidth based on [Calonico et al. \(2017\)](#). *Source:* COAR administrative data 2015–2019; SIAGIE system 2014-2018.

Tables

Table A.1: COAR Applications Process

	2015	2016	2017	2018	2019
Grade 8 enrollment					
Schools	8754	8908	9094	9272	9401
Students	400109	397141	405991	417239	428657
Eligibility					
Schools	6231	6957	7348	7641	7914
Students	15139	17574	39783	42711	45510
Applications					
Schools	3001	4514	5506	5641	6017
Students	6330	10403	25728	27161	30690
Second-round applications					
Schools	1990	2959	2321	2763	2499
Students	3307	5053	5659	5400	6220
Admission					
Schools	1139	1646	1451	1668	1508
Students	1602	2412	2700	2701	2701
Enrollment					
Schools	1101	1604	1451	1665	1506
Students	1543	2352	2700	2687	2709
COAR schools	14	22	25	25	25

Notes: The table presents the number of public schools and students enrolled in those schools in grade 8; the number of eligible students, applicants, second round applicants, students admitted and enrolled to the COAR system and their corresponding origin schools per year during the 2015-2019 period. It also includes the number of COAR schools in operation each year. *Source:* COAR administrative data 2015–2019; SIAGIE 2014–2018.

Table A.2: Departmental Quotas used in the COAR Admission Process

	2016	2017	2018	2019
Lima	180	210	240	240
Callao	10	20	20	20
Ancash	40	70	80	80
Tumbes	10	70	80	80
Other 21 departments	60	70	80	80

Notes: The table shows the predefined admissions quota assigned to each department by year. See Section [4.2](#) for more details.

Table A.3: Characteristics of Schools in and out of the Sample

Variable	Schools in sample	Schools out of sample	
Students enrolled in grade 8 (#)	72.752 (74.184)	25.483 (32.733)	-47.268*** (0.887)
Female students (share)	0.487 (0.153)	0.464 (0.185)	-0.024*** (0.003)
Native Spanish speakers (share)	0.837 (0.308)	0.834 (0.341)	-0.003 (0.006)
Students with lowly educated parents (share)	0.893 (0.122)	0.791 (0.267)	-0.102*** (0.004)
Eligible students (share)	0.160 (0.123)	0.072 (0.137)	-0.087*** (0.002)
Urban (share)	0.821 (0.383)	0.369 (0.483)	-0.452*** (0.009)
Distance to nearest COAR (kms)	59.710 (45.504)	59.647 (50.478)	-0.062 (0.919)
District population size (thousands)	91.659 (175.839)	134.685 (211.944)	43.026*** (3.791)
District poverty rate (share)	42.505 (24.185)	39.925 (25.833)	-2.580*** (0.478)
Observations	3,909	10,745	14,654

Notes: The table compares the means of characteristics of schools included in the main sample and those schools out of the sample. The main sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. Column 3 shows the difference in means. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015–2019; SIAGIE system 2014–2018; 2017 Population Census.

Table A.4: Summary Statistics

	(1) Schools in sample mean/sd	(2) Schools in CCT Bandwidth mean/sd
Panel A. Characteristics of the best ranked applicant in the school		
Female	0.57 (0.49)	0.58 (0.49)
Mother tongue is Spanish	0.88 (0.32)	0.89 (0.31)
Lowly-educated parent	0.70 (0.46)	0.66 (0.47)
Panel B. Characteristics of school of origin		
Students enrolled in grade 8 (share)	71.25 (72.96)	76.43 (79.50)
Female students (share)	0.49 (0.16)	0.49 (0.17)
Native Spanish speakers (share)	0.83 (0.32)	0.84 (0.31)
Students with lowly educated parents (share)	0.90 (0.12)	0.89 (0.13)
Eligible students (#)	3.47 (2.13)	3.34 (1.95)
Applied (#)	2.64 (1.62)	2.62 (1.58)
Accepted to 2nd round (#)	1.51 (0.81)	1.63 (0.90)
Admitted (#)	0.58 (0.79)	0.74 (0.86)
Urban school (share)	0.82 (0.38)	0.84 (0.37)
Distance to nearest COAR (kms)	72.62 (63.04)	79.30 (71.05)
District population size (thousands)	91.89 (175.85)	65.22 (128.30)
District poverty rate (%)	42.50 (24.17)	43.18 (23.96)
Observations	3909	2410

Notes: The table describes the characteristics of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. Column 2 reports observations within the optimal bandwidth proposed in [Calonico et al. \(2017\)](#) obtained by the estimation of equation [2](#). *Source:* COAR administrative data 2015–2018; SIAGIE system 2014–2017; 2017 Population Census.

**Table A.5: Effect of Older Schoolmate on COAR Applications the Following Year :
Alternative Specifications**

	(1) At least one applied	(2) Applied	(3) Accepted to 2nd round	(4) Admitted
Panel A. No baseline covariates				
Older schoolmate is admitted	0.0603** (0.0299)	0.505* (0.258)	0.128 (0.116)	0.151* (0.0830)
Observations in bandwidth	2552	2249	2077	2375
Mean D.V. control	0.852	3.039	0.935	0.404
	(1) At least one applied	(2) Applied	(3) Accepted to 2nd round	(4) Admitted
Panel B. SE clustered at the district level				
Older schoolmate is admitted	0.0460 (0.0297)	0.521** (0.240)	0.179* (0.103)	0.176** (0.0824)
Observations in bandwidth	2071	1998	1988	2252
Mean D.V. control	0.852	3.038	0.940	0.407
	(1) At least one applied	(2) Applied	(3) Accepted to 2nd round	(4) Admitted
Panel C. RV is admission rank				
Older peer is admitted	0.0734*** (0.0243)	0.419*** (0.137)	0.351*** (0.0833)	0.237*** (0.0736)
Observations in bandwidth	2356	2311	2396	2256
Mean D.V. control	0.877	2.562	1.177	0.559

Notes: The table presents the RD estimates of the effect of an older schoolmate's admission to COAR on school-level applications the following year (see equation 2). The estimates are obtained from a local linear regression using the optimal bandwidth based on Calonico et al. (2017). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. The number of observations and the mean of the dependent variable among non-admitted applicants are reported below each coefficient. *** $p < 0.01$,

** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015–2019.

Table A.6: Effect of Older Schoolmate on COAR Applications by Socioeconomic Similarity

	Top applicant in t-1 has a lowly educated parent		Top applicant in t-1 has a highly educated parent	
	(1) Applicants with lowly educated parent	(2) Applicants with highly educated parent	(3) Applicants with lowly educated parent	(4) Applicants with highly educated parent
Older schoolmate is admitted	0.377 (0.239)	-0.0362 (0.103)	1.014*** (0.386)	0.151 (0.187)
Observations in bandwidth	1631	1306	471	604
Mean D.V. control	2.429	0.611	1.479	0.740

Notes: The table presents the RD estimates of the effect of an older schoolmate's admission to COAR on the number of students that applied to COAR the following year by socioeconomic similarity. The estimates are obtained from a local linear regression using the optimal bandwidth based on [Calonico et al. \(2017\)](#). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. It is split into older students with a poorly educated parent and a highly educated parent. The number of observations and the mean of the dependent variable among non-admitted applicants are reported below each coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015–2019; SIAGIE system 2014-2018.

Table A.7: RD Estimates: Effect of Older Schoolmate on COAR Applications: Excluding the 2018 cohort

	(1) At least one applied	(2) Applied	(3) Accepted to 2nd round	(4) Admitted
Panel A. Number of students				
Older schoolmate is admitted	0.0287 (0.0362)	0.584** (0.246)	0.154 (0.118)	0.147 (0.0910)
Observations in bandwidth	1486	1967	1727	1892
Mean D.V. control	0.873	2.975	1.056	0.464
Panel B. Share of eligible students				
Older schoolmate is admitted		0.0679* (0.0350)	0.0408 (0.0253)	0.0209 (0.0226)
Observations in bandwidth		1836	2406	2012
Mean D.V. control		0.641	0.269	0.125

Notes: The table presents the RD estimates of the effect of an older schoolmate’s admission to COAR on the number of students that applied and the number of students admitted to COAR the following year excluding the 2018 cohort. The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2017 period. The number of observations and the mean of the dependent variable among non-admitted applicants are reported below each coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015–2019.

Table A.8: Effect of Older Schoolmate on COAR Admission Exam Scores by Parental Education

	(1) Lowly educated parent	(2) Highly educated parent
Older schoolmate is admitted	-0.00484 (0.0754)	0.140 (0.116)
Observations in bandwidth	1617	925
Mean D.V. control	-0.146	0.209

Notes: The table presents the RD estimates of the effect of an older schoolmate’s admission to COAR on the performance of younger applicants in the COAR admission exam by parental education. The estimates are obtained from a local linear regression using the optimal bandwidth based on [Calonico et al. \(2017\)](#). The sample consists of schools with at least one applicant who reached the second round of the COAR admission process for the first time during the 2015-2018 period. The number of observations and the mean of the dependent variable among non-admitted applicants are reported below each coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* COAR administrative data 2015-2019.