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School Effects on College Outcomes in the Absence of Standardized Tests: The Role of Reputation vs Effectiveness

Román Andrés Zárate
Martín Carbajal
María Pía Basurto
Manuel Barrón

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MIT Department of Economics
77 Massachusetts Avenue, Bldg. E53-390
Cambridge, MA 02139

National Bureau of Economic Research
1050 Massachusetts Avenue, 3rd Floor
Cambridge, MA 02138

School Effects on College Outcomes in the Absence of Standardized Tests: The Role of Reputation vs. Effectiveness*

Román Andrés Zárate   Martín Carbajal   María Pía Basurto   Manuel Barrón

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Abstract

Without standardized tests, college admissions may reward high schools' reputation over effectiveness—a phenomenon we study in Peru. We first estimate the impact of selective public exam schools on college outcomes by leveraging the admissions mechanism in a single- and multiple-offers RDD. Despite no conclusive evidence of learning gains, graduating from exam schools significantly improves college applications, admissions, and enrollment, particularly at top private universities. Exam school graduation signaling students' abilities is an important mechanism explaining these effects. Evidence of marginally obtaining the International Baccalaureate Diploma reinforces this signaling mechanism. We then develop and validate causal value-added models to assess the impact of all secondary schools on college outcomes. In line with exam school effects, value-added in learning does not predict a school's impact on college outcomes after controlling for average graduates' characteristics. These findings highlight the critical role of information frictions in perpetuating inequality and the importance of allowing talented low-income students to signal their skills.

*The authors' order is reverse alphabetical order. Corresponding author: Román Andrés Zárate, Department of Economics, University of Toronto, email: ra.zarate@utoronto.ca. Martín Carbajal, Department of Economics, Arizona State University, email: macarba3@asu.edu. María Pía Basurto, Department of Economics, Universidad del Pacífico, email: basurto_mp@up.edu.pe. Manuel Barrón, Department of Economics, Universidad del Pacífico email: mf.barrona@up.edu.pe. We are grateful to Alberto Trelles for excellent research assistance. This research uses administrative data from the Ministry of Education of Peru. We thank public officials for their support in granting access and explaining this data. The paper has benefited from comments at multiple seminars and conferences. We are especially thankful to Carolina Arteaga, Rahul Deb, Joaquín Klot, and Román David Zárate for helpful comments. All remaining errors are our own.

1 Introduction

The role of standardized tests in college admissions is a contentious issue (Harper, 2023; Zwick, 2023). Proponents argue that these tests provide a standardized, meritocratic measure across diverse applicants, which can help talented low-income students (Chetty et al., 2023). Critics, however, claim that standardized tests can perpetuate inequalities, being influenced by socioeconomic status, race, test preparation, and biases (Jacob and Rothstein, 2016). They also argue that standardized tests may not predict college success better than high school grades (Rothstein, 2004). While recent studies have examined the effects of removing standardized tests on students' high school academic investments (Borghesan, 2023), the aggregate consequences of removing standardized tests from college admissions remain an ongoing inquiry.

Removing standardized tests from college admissions could lead to a greater reliance on alternative information sources, like the reputation of the graduating high school. While evidence from the US shows that school value-added on test scores aligns with value-added on longer-term outcomes, such as college enrollment (Dynarski et al., 2013; Angrist et al., 2016, 2023), without test scores, admissions authorities cannot directly observe the learning gains from effective schools. Instead, universities may infer applicants' abilities from their high school reputation. The shift from effectiveness toward reputation could reinforce inequalities as students from disadvantaged backgrounds have fewer opportunities to graduate from prestigious schools. The absence of standardized tests could also introduce further information frictions, as a school's effectiveness in enhancing learning might not directly translate into longer-term outcomes.

In this paper, we study school effects on college outcomes in Peru, analyzing how these effects relate to the school's reputation—measured by the average characteristics of their graduates—and its effectiveness in improving learning. Peru presents a distinctive context to explore this question due to the absence of a standardized school exit test, which forces college admission authorities to collect alternative measures of students' abilities or rely on existing sources of information, including the graduating high school. While Peru has nationwide standardized tests, they are usually low-stakes, taken three and eight years before high school graduation, and hold no bearing on college admissions decisions. Yet, these tests allow to explore the connection between school reputation and effectiveness in shaping schools' effects on college outcomes.

To explore this connection, we leverage a comprehensive dataset with information on students' applications, admissions, and enrollment across nearly all universities in Peru. This dataset is particularly valuable because it distinguishes between the various admission methods employed by universities. In Peru, universities collect alternative measures of ability or use existing information, such as school grades, to make admission decisions. Consequently, three primary admission modes are prevalent: (i) the exam admission mode, where applicants take a university-specific admission test; (ii) the extraordinary admission mode, which provides benefits to applicants who meet specific conditions set by each university and often exempts them from the admission exams; and (iii) preparatory academies, where participants take preparatory courses offered by the university, with top students receiving direct admission.

Descriptive evidence shows that students from advantageous socioeconomic backgrounds benefit the most from extraordinary admissions. Top private universities also use this admission mode more frequently than public universities. Around 50% of students from schools in the top 1% of the income distribution are admitted to private institutions through extraordinary admissions, compared to less than 5% for students from schools in the bottom half.

Motivated by this evidence, we estimate school effects on college outcomes, considering the different admission modes. First, we assess the causal impact of selective public exam schools, the *Colegios de Alto Rendimiento* (COAR) Network, on college outcomes. The COAR Network comprises 25 public high schools, one in each region of Peru, branded as an elite education for the most talented low-income students in the country. They mirror a similar model to selective exam schools in the US (Abdulkadiroğlu et al., 2014; Dobbie and Fryer, 2014) and other countries (Lucas and Mbiti, 2014), limiting applications to students at the top of their class, using a series of tests for admissions, and fostering interaction among high-achieving peers.

To identify the causal effects of the COAR Network, we use the government's assignment mechanism in a fuzzy regression discontinuity design (RDD). Similar to other school assignment mechanisms (Abdulkadiroğlu and Sönmez, 2003; Pathak and Sönmez, 2008), the COAR mechanism lacks some theoretical properties. However, like the deferred-acceptance (DA) algorithm, it uses applicants' types—preferences and priorities—and an admission score to assign first-round offers. The mechanism generates three cutoffs for each applicant: a region-specific general cutoff for any COAR school offer and 1st- and 2nd-choice cutoffs for specific COAR school offers.

The variation in offers around these cutoffs is the basis for an RDD, which must address two sources of selection bias. First, like in a typical RDD, controlling for the running variable and comparing applicants within a bandwidth around admission cutoffs accounts for non-random admission scores. Second, non-parametric conditioning on the applicant's type addresses selection bias from preferences and priorities. In practice, however, as only a few observations share the same type, Abdulkadiroğlu et al. (2017a) suggest conditioning on the propensity score of each school offer. Our empirical strategy builds on Abdulkadiroğlu et al. (2022), who characterize the propensity score for DA with multiple lottery and non-lottery tie-breakers, to define the vector of propensity scores for the COAR mechanism.

We leverage the assignment mechanism in a single-offer and multiple-offers fuzzy RDD. Our first strategy is a typical fuzzy RDD, where clearing the general admission cutoff is an instrument for COAR graduation. As general admission cutoffs only depend on the applicant's region of origin, we control for applicants' type by conditioning on this variable, with running variable controls also varying by region. Our second strategy leverages all the variation in first-round offers from the assignment mechanism using the school-specific offers, determined by the three cutoffs, as instruments for COAR graduation. Instead of fully conditioning on applicants' type, we account for selection by controlling for the vector of school-specific propensity scores.

The first-stage estimates show that receiving a COAR offer strongly predicts COAR graduation and the baseline scores of peer graduates. In the single-offer model, clearing the general admission cutoffs increases peer graduates' average math scores by 1.65σ (standard error (s.e.) 0.057) and reading scores by 1.37σ (s.e. 0.051). Since universities do not have access to the COAR admission test, we hypothesize that they infer applicants' abilities from the differences in peer graduates baseline scores.

Graduating from the COAR Network improves college outcomes, especially at top private universities, with extraordinary admissions accounting for 40% to 60% of these effects. Marginally admitted COAR graduates are 11.9 percentage points (p.p.) (s.e. 5.4 p.p.) more likely to attend college, with consistent results in both single- and multiple-offers models. These effects are driven by top private institutions, with a 15.8 p.p. increase (s.e. 3.8 p.p.) in top-10 private enrollment in the single-offers model and 9.4 p.p. (s.e. 2.2 p.p.) in the multiple-offers model. In terms of admission mode, the multiple-offers model shows that COAR graduates are 24.6 p.p. (s.e. 3.5 p.p.) more likely to apply and 15.0 p.p. (s.e. 3.0 p.p.) more likely to be admitted through extraordinary admissions at private universities, mainly in top-10 institutions.

We then examine the mechanisms behind these effects, providing evidence that universities use the graduating school as a signal of applicants' abilities. Although COAR schools differ from traditional public schools in many ways, including peer quality, the evidence of COAR's impact on human capital is, at best, inconclusive. A previous evaluation using a similar single-offer RDD strategy found no impact on test scores and non-cognitive skills (Hatrick and Paniagua, 2021). Additionally, after adjusting for differential selection in admission exams, our estimates show no effect of COAR graduation on university-specific exam scores. The estimates are similar in magnitude and precision to previous studies finding little evidence of elite schools improving learning outcomes.

We also present additional empirical exercises that directly support the signaling mechanism. As COAR effects on admissions could result from students' application choices, we test for signaling by examining COAR's impact on eligibility for extraordinary admissions. We focus on two types: whether the graduating school is on the list of eligible schools for extraordinary admissions and whether the university allows special admissions for applicants with the International Baccalaureate (IB) degree, which COAR schools also offer.

Graduating from a COAR school increases the number of institutions allowing extraordinary admissions. COAR graduates are eligible to apply to about 28 more universities (s.e. 0.106) and 4.2 (s.e. 0.062) more top-10 universities via extraordinary admissions, with 30% to 50% of these being private institutions.[1] Additionally, after accounting for whether marginally admitted COAR graduates received the IB diploma, they are eligible to apply to 5.24 more private (s.e. 0.788) and 1.13 more public universities (s.e. 0.170) through the IB.

Our final exercise for the signaling mechanism reveals that top private universities also use the IB diploma as a signal of applicants' skills. We compare COAR students who marginally earn the IB diploma by scoring 24 points with those who missed it by one point. This within-school comparison shows balance across various academic and non-cognitive skills, indicating that receiving the IB is the only difference between the two groups. The results support the signaling hypothesis: earning the diploma increases extraordinary admissions by 10.7 p.p. (s.e. 3.8 p.p.) and enrollment by 17.3 p.p. (s.e. 4.7 p.p.) at top-10 private universities.

We then examine the relationship between school effects on college outcomes, school reputation, and learning effectiveness for other schools in Peru. We estimate school value-added models on college outcomes, flexibly controlling for math and reading achievement, socioeconomic con-

[1] Interestingly, while more public universities offer special admissions for COAR graduates, the limited number of available slots—only one or two—explains the larger overall effects at private institutions.

ditions, and parental and household characteristics three years before high school graduation. To validate these value-added estimates, we compare them against the quasi-experimental variation from the multiple-offers COAR model, following the test developed by Angrist et al. (2017). This analysis supports the validity of our school value-added estimates for college enrollment and admissions at private universities. We perform additional validation tests, finding minimal influence from unobservable factors on the school value-added estimates.

After validating the value-added estimates, we explore the link between these effects and school reputation, measured by average test scores and socioeconomic background. We quantify school effectiveness on learning using value-added to test scores from 2nd grade in primary to 2nd grade in secondary school. The analysis shows that, after controlling for average scores and socioeconomic background, school effectiveness on learning does not predict college outcomes, particularly at private universities. Instead, the main driver of variation in school effects on college outcomes is the average socioeconomic background, which is also the key predictor of eligibility for extraordinary admissions at top private universities.

Since a school's average socioeconomic background determines eligibility for extraordinary admissions, we compare eligible schools with three groups: (1) schools with similar value-added on test scores, (2) schools with similar average graduates' scores, and (3) COAR schools. Our findings reveal significant differences in value-added on college outcomes between eligible schools and the first two groups, particularly at top private universities and through extraordinary admissions. In contrast, the differences between eligible and COAR schools are minimal or even favor COAR schools. While COAR schools show little evidence of enhancing human capital, they enable talented low-income students to signal their abilities, reducing income gaps in college quality and market segregation.

Our findings contribute to four areas of literature. First, they add to the research on elite schools, showing that public elite schools can improve college outcomes even without significant human capital gains. While some studies have shown that access to higher-achieving schools can benefit students (Pop-Eleches and Urquiola, 2013), most evidence from elite public schools—in the US (Abdulkadiroğlu et al., 2014; Dobbie and Fryer, 2014; Barrow et al., 2020), Europe (Behaghel et al., 2017), and developing countries (Lucas and Mbiti, 2014)—indicates no major gains in academic achievement. Furthermore, even when test score improvements are observed, they can come with drawbacks like higher dropout rates (Dustan et al., 2017) and reduced self-confidence (Fabregas, 2017). Our study extends this literature by demonstrating that, in contexts lacking comparable skill measures, elite public schools can still positively impact long-term outcomes by helping talented students signal their abilities.

Second, this study adds to the literature on school effects on longer-term outcomes. While previous research indicates that school effects on short-term outcomes like test scores can predict longer-term outcomes (Angrist et al., 2016), our findings suggest a more complex relationship in contexts without standardized testing. Recent studies examine whether parents' school preferences are influenced more by reputation or actual effectiveness (Abdulkadiroğlu et al., 2020; Beuermann et al., 2022). Our results suggest similar frictions affect university admissions authorities, who seem to favor prestigious schools over effective ones.

Third, our results add to the evidence on policies aimed at improving equity in higher education access. While most research has focused on the impact of financial aid and scholarship programs on college enrollment and completion for low-income students (Bucarey et al., 2020; Solis, 2017; Angrist et al., 2021; Londoño-Velez et al., 2023), our findings suggest that providing opportunities to signal talent can also enhance college outcomes. Our results align with recent US evidence showing that high-income students disproportionately benefit from non-academic admissions, with higher impacts for graduates of affluent private schools (Chetty et al., 2023).

Finally, our results contribute to the debate on whether education returns are driven by signaling (Spence, 1973) or human capital. While much of the empirical evidence on signaling has focused on alternative high school degrees (Jepsen et al., 2016), college reforms (Arteaga, 2018), and labor market outcomes (MacLeod and Urquiola, 2015; MacLeod et al., 2017; Sekhri, 2020), our findings extend this discussion to college admissions. In settings where admissions have limited information about applicants' true potential, they may rely on available signals such as the graduating school or prestigious credentials like the IB diploma, creating further information frictions in education markets.

The rest of this paper is organized as follows. Section 2 describes the education market in Peru. Section 3 presents the data. Section 4 documents COAR effects on college outcomes and explores the main mechanisms. Section 5 extends the analysis to other secondary schools, and Section 6 concludes.

2 Education in Peru

2.1 Primary and Secondary School

The K-12 education system in Peru has two main stages: primary and secondary school. Primary school spans six academic years and enrolls approximately 3.5 million students aged between 5 and 12. Secondary school lasts five years and serves about 2.5 million students aged 12 to 18. Students can attend four main types of schools: (i) regular public schools, (ii) selective public schools, and (iii) private schools, or (iv) charter schools.

Regular public schools are free and accessible to all students nationwide, with school assignments primarily based on proximity. Parents have limited choice in selecting a public school. Variation in teachers, peer quality, and resources across public schools is low and mainly depends on geographic location.

The second type of school are selective public exam schools: the *Colegios de Alto Rendimiento* (COAR) Network. COAR schools are selective public boarding schools operating for the last three years of high school and target low-income high-achieving students. The first COAR opened in Lima in 2010, and due to popular demand, the Network expanded by 2017 to 25 schools, one per region, up from 14 schools in 2015 and 22 in 2016. COAR schools feature excellent facilities, including libraries and scientific labs, and run extended hours of 60 pedagogical hours per week. The government covers all services, such as food and laundry, and provides accepted students with all school materials, including uniforms and a personal laptop. Students also have the opportunity to earn the prestigious International Baccalaureate (IB) diploma. Teachers are hired under special contracts and work longer hours for higher pay than regular public school teachers.

Admissions to the COAR Network are highly competitive, with only top students from public schools being eligible to apply. The process has a two-phase evaluation: (i) a written test with a math and a reading component, and (ii) a social activities test and an interview assessing non-academic skills. Admission depends on a composite score from these tests, regional quotas, and student preferences. Section 4.1 explains in detail the admission process.

The third and fourth school options available to parents are private and charter schools. Private schools outperform public schools, on average, but they have more variation in performance and inputs. Private schools offer a wide array of choices, differing in tuition, peer characteristics, teachers, and facility quality. Around 25% of students in secondary school attending private schools. Allende (2019) examines how social interactions influence market power and strategic behavior of private schools in Peru. A final option for parents are charter schools. The charter sector constitute less than 2% of all schools.

Standardized tests in Peru are relatively recent, with only two nationwide assessments during our study period. The first, introduced in 2006, targets 2nd-grade primary school students. The second, starting in 2015, assesses 2nd-grade students in secondary school (three years before high school graduation). These tests are typically low-stakes, with no individual scores provided to students[2] and no university including them in their admission decisions.

2.2 College Market

Throughout the paper, we refer to college as the equivalent of an undergraduate degree in the US and to universities as the institutions offering such degrees. Like the school market in Peru, the college market also comprises private and public providers, with private universities varying in tuition fees and quality. While most private universities usually charge different tuition fees depending on a student's socioeconomic background, public universities receive the same resources from the government for each student. The government also offers scholarships to low-income students, which they can use in certified public or private universities. The government has introduced several measures to ensure university quality, including creating an entity to monitor universities and publishing rankings, which we use to classify institutional quality.

University admissions are decentralized. Due to the absence of a high school exit standardized test, universities either conduct their own admissions test or rely on existing information for admissions. Most universities have their own admission exam and use a cutoff system based on the number of available slots in each program.

Many private universities have introduced an alternative admission method known as extraordinary admissions, which benefits applicants who meet specific criteria determined by each university. In many cases, applicants can entirely waive the admission exam and receive direct admission into the university. In other cases, candidates are evaluated via alternative methods, such as interviews or essays. On average, admission rates under this type of admission are higher

[2]In some cases, parents and students can receive information on the individual achievement level in the test, which has four categories: (i) before beginning, (ii) beginning, (iii) developing, and (iv) satisfactory. According to a household survey, only around 35% of parents recall receiving such information for students enrolled in 2nd grade of primary school, and the proportion for secondary schools is even lower as only 20% of parents recall receiving such information.

than regular admission exams.

The criteria for extraordinary admissions vary among institutions, often including the applicants' secondary school. For instance, some universities grant automatic admission to students from specific high schools if they rank in the top half or top third of their class. Appendix Figure A.1 presents a specific example. Additionally, many universities favor applicants from schools offering the IB program, providing immediate admission to applicants with the diploma.

The third type of admission is preparatory academies. Preparatory academies are parallel institutions associated with each university that prepare students for the university-specific admission exam and the initial coursework at each institution. These programs usually last between two to six months, and students typically pay an enrollment fee. Top students usually receive direct admission to the university, while other students must apply via the regular admission exams. Anecdotal evidence suggests that academies are an alternative source of revenue for all universities, including public ones.

3 Data and Descriptive Evidence

3.1 Data

We combine various administrative data sets to track students' progress from primary school to college. We first provide a general overview of these datasets and their main use in our analysis. We then describe our sample of analysis for Section 4, which explores COAR effects on college outcomes, and for Section 5, which extends the analysis to other schools in Peru. Appendix B provides more details and the matching rates across multiple data sets.

1. COAR application files: The first data set we use are COAR application files between 2015 and 2017. These files have information on applicants' performance at the different stages of the admission process, preferred COAR schools, and relevant information for the assignment mechanism, including the region of origin. The files also have information on first-round offers, which we use to validate our replication of the assignment mechanism. The primary use of this data set is estimating COAR effects on college outcomes.

For two cohorts of COAR students (2015 and 2016), we also have information about the IB, including their total score and whether they earned the diploma. We also have more measures of academic and non-academic outcomes for these students, including personality and social network surveys (Zárate, 2023). We use this additional data to validate the research design and estimate the effects of the IB diploma.

2. School enrollment files: Our second main data set corresponds to school enrollment files between 2013 and 2019. Such files allow us to track school enrollment in primary and secondary schools for all students in Peru during this period. Besides enrollment, these files provide additional information such as dropout, retention, and transcripts. We use these data sets to identify COAR applicants' sending and counterfactual schools and the graduating school for all students in the country.

3. National standardized tests (ECE): The third and fourth main data sets are standardized national-wide census tests in 2nd grade in primary and secondary school, respectively. Both tests are low-stakes for students with no consequence for the college admission process. Standardized tests for 2nd grade in primary school (9 years before high school graduation) are available between 2007 and 2016, and for 2nd grade in high school (3 years before graduation) between 2015 and 2019. In addition to math and reading performance, which allows us to characterize their academic abilities, the 2nd-grade secondary test files also have rich survey demographic information, including parental education, dwelling conditions, and household assets. The Ministry of Education summarizes such information in a socioeconomic index that we use to characterize students' socioeconomic background.

We use these data sets for two purposes. First, for the 2016 and 2017 cohorts of COAR applicants, these standardized tests provide a nationwide comparable measure of academic ability to test for balance. Second, in the general analysis of school effects in Section 5, we use these data sets to control for baseline scores. Specifically, we estimate school value-added models on learning by matching primary to secondary school test scores. We also control for test scores in the school value-added models on college outcomes.

4. College applications and enrollment files: The final two data sets are college application and enrollment files for all public and private universities in Peru from 2017 to 2022. The application files have rich information on each student-university application, including the application period, the score obtained by the applicant, and the final admission decision. Critical for our study, it also has information on the application mode. Distinguishing between applicants admitted via exams and alternative methods is critical to explore mechanisms driving school effects on college outcomes. The enrollment files have information on final enrollment decisions.

We use application and enrollment files to construct college outcomes that capture students' applications, admissions, and enrollment. We differentiate between public and private institutions and use the government ranking to classify the top 10 universities as a measure of institutional quality. For application and admission outcomes, we further distinguish between exam-based and other admission modes. Data Appendix B offers more details on the match between the application, admissions, and enrollment files.

Sample of analysis: For the COAR Network effects in Section 4, our *COAR Sample* includes all COAR applicants from 2015 to 2017. The second sample, the *All Schools Sample*, is used to estimate other school effects in Section 5 and consists of students in 2nd grade of secondary school in 2015 and 2016, who took the nationwide standardized test. These samples overlap for the 2016-17 COAR cohorts. For the 2015 COAR cohort, there's no national standardized test since it was first implemented when they were already in 3rd grade. Estimates of COAR effects are similar when excluding this cohort, though the smaller sample size reduces statistical power.

3.2 Descriptive Evidence

This section presents some descriptive evidence of universities' admissions and their relationship to average school characteristics. We first examine how admission modes vary by university characteristics. Panel A of Table 1 shows the proportion of each admission mode across public and private universities and by the institutional ranking. There is significant variation in admission policies between public and private universities, particularly among the top 20. While the average rate of admission via exams is around 67% for top-10 and 77% for top-20 public universities, it drops to 37% and 39% for top-10 and top-20 private universities. Notably, about 55% of admitted students at top-20 private institutions are through extraordinary admissions, compared to less than 10% at public institutions. Public universities have more preparatory admissions than private ones, while lower-ranked universities show similar admission mode rates between public and private institutions.

These admission policies and the type of university students attend can influence long-term labor market outcomes. Although estimating university effects on employment and wages is beyond this paper's scope, Appendix Figure A.2 shows average first-job wages by university type and ranking. Private universities in the top 20, which predominantly use extraordinary admissions, have higher average wages than similarly ranked public universities and lower-ranked private and public institutions.

Next, we explore how different admission modes relate to average school characteristics. We merge the 2015-16 standardized test data, which include test scores and socioeconomic information three years before high school graduation, with university applications and admissions. This allows us to characterize the average socioeconomic index of the graduating school and the proportion of students admitted to each university through various admission modes.

Figure 1 reports average unconditional admission rates at private (Panel A) and public (Panel B) universities for high school graduates, grouped by each percentile (100 groups) of the average school socioeconomic index. Appendix Figure A.3 shows the correlation between the average socioeconomic index percentile and the school type. Most schools at the bottom of the distribution are public, while private schools are exclusively prevalent at the top.

The evidence in Figure 1 reveals persistent income segregation from high school to college. Most students graduating from schools at the bottom of the average socioeconomic index distribution, who graduate from public schools, are not admitted to any university. In contrast, students from schools in the middle of the distribution up to the percentile 98% have admission rates at public universities (Panel B) that range between 5 to 15%, mainly through admission exams, with preparatory academies as the second most common admission mode. Although there is a slight positive correlation between the school percentile and the admission rates, the relationship is relatively flat.

In contrast, Panel A shows a clear correlation between admission rates at private institutions and the school percentile. The difference in this correlation between exam and extraordinary admissions is striking. Exam admissions show a linear trend, while for extraordinary admissions, the curve is fairly convex, indicating that graduates at the top of the distribution benefit disproportionately from this type of admission. For the 100th percentile, more than half of the students are admitted through extraordinary admissions at a private university. This rate decreases to around 40% for the 99th percentile and is only about 20% for the 90th percentile. This evidence suggests that extraordinary admissions are mainly used by top private institutions and primarily benefit students from schools at the top of the income distribution.

As we estimate COAR effects on college outcomes, Figure 1 also shows average admission rates for COAR schools, marked by triangles. COAR schools mainly serve middle-income students, with their average socioeconomic index ranging from the 53rd to the 74th percentile.

Notably, exam and extraordinary admissions at both private and public universities are relatively high for COAR schools. For example, some COAR schools have extraordinary admission rates comparable to other schools above the 90th percentile of the socioeconomic index. Extraordinary admission rates at public universities are higher for COAR schools than for other schools in the distribution. While this descriptive evidence is promising, it cannot be interpreted as causal. The next section explores COAR causal effects on college outcomes.

4 COAR Network Effects

This section estimates COAR effects on college outcomes and explores the main mechanisms behind such effects.

4.1 Assignment Mechanism

We first describe the COAR assignment mechanism and its role in our research design. Similar to other school assignment mechanisms (Abdulkadiroğlu and Sönmez, 2003; Pathak and Sönmez, 2008), the COAR mechanism has significant flaws, such as not being strategy-proof and restricting students' preferences. However, our primary interest lies in the variation in school offers it generates to estimate COAR causal effects, rather than in its theoretical properties.

Like other school choice problems, the COAR assignment problem is defined by a set of applicants, schools, and school capacities. Let $\mathcal{I}$ denote a set of applicants indexed by i, with a size of n, and let $\mathcal{S}$ denote the set of schools with $s = \{0, 1, \cdots, S, p\}$ indexing schools, where $s = 0$ represents an outside option, which in our case is a traditional public school, and $s = p$ indicates a pending first-round offer, as some applicants are offered a COAR seat but not in a specific school.[3] Seats at schools are constrained by a capacity vector $\mathbf{q} = \{q_0, q_1, \cdots, q_S\}$, with $q_0 > n$, so that all applicants can remain in a traditional public school, and $Q = \sum_{s=1}^{S} q_s$ indicating the total number of slots in the COAR Network.

An assignment function $\tilde{\mu} : \mathcal{I} \to \mathcal{S}$, allocates each applicant $i \in \mathcal{I}$ to a first-round offer from a COAR school ($s \in \{1, \cdots, S\}$), to a pending offer, p, or to 0 indicating that the applicant must remain in a traditional public school. The COAR mechanism, denoted by μ, uses three main inputs for the assignment: applicants' priorities, their preferences, and admission scores.

The only variable determining schools' priorities for students is the region of origin. Let $l_i \in \mathcal{L}$ represent the applicant's region, with $l_i = 1, \cdots, S$ indicating regions with a COAR school and $l_i > S$ indicating regions without one. The region is crucial since the government assigns each region a quota for overall COAR slots. For 1st-choice offers, school s prioritizes applicants from their own region ($l_i = s$), while applicants from regions without a COAR school ($l_i > S$) are grouped together and considered as a separate group. Let w_i be a binary variable indicating if the applicant's region has a COAR school: $w_i = 1$ if $l_i \leq S$, and 0 otherwise.

The second factor determining an applicant's type is their vector of preferences. In the COAR mechanism, applicants rank exactly two COAR schools, with c_{1_i} and c_{2_i} representing the first and second choices, respectively. The government imposes specific constraints on these

[3] The number of schools vary by year due to the COAR expansion over time, with 15 schools available in 2015, 23 in 2016, and 25 in 2017.

preferences. Applicants from regions with a COAR school ($l_i \leq S$) must list their regional school as their first choice ($c_{1_i} = l_i$) and can choose their second option freely. In contrast, applicants from regions without a COAR school ($l_i > S$) can rank any two schools without restrictions.

The final input of the mechanism is the vector of applicants' scores in the COAR admission exams, denoted by r_i. This score is a composite of three tests in the admission process: a math and reading comprehension written test, an interview, and a social skills assessment. We assume $supp(r_i) = [0, \overline{R}]$ with $\overline{R} < \infty$.

Similar to DA with non-lottery tie-breakers (Abdulkadiroğlu et al., 2022), the COAR mechanism assigns applicants to COAR seats based on their type $\theta_i = (l_i, c_{1_i}, c_{2_i})$—the combination of region of origin and preferences—and a non-lottery tie-breaker, r_i, which is the composite score in the COAR admission tests. The COAR assignment mechanism uses these inputs to allocate first-round offers in two phases: assigning any COAR offer and assigning school-specific offers.

The details of the algorithm are in Appendix C, but we briefly outline its steps for assigning 1st-round offers, which is the quasi-random variation used in our empirical design. In the first step, the algorithm assigns offers to join any COAR school by selecting an admission quota for each region $l \in \mathcal{L}$. Applicants are ranked by r_i within regions, and the region-specific quota sets a general admission cutoff, $\tau_0(l_i)$. Applicants who clear this cutoff receive an offer to join any COAR school. This quota is defined for all regions, whether they have a COAR school or not.

In the second step, the algorithm assigns school-specific offers. It first allocates 1st-choice offers to applicants from regions with a COAR school by setting a same-region quota for all schools. Then, it assigns 1st-choice offers to applicants from regions without a COAR school by grouping and ranking them by r_i within their first choice. This process results in a 1st-choice cutoff for each applicant, $\tau_1(w_i, c_{1_i})$, which depends on whether they apply from a region with a school (w_i) and their first choice (c_{1_i}).

In the next step, the algorithm assigns 2nd-choice offers by ranking all applicants who were rejected from their first choice within their second choice. If the second choice is oversubscribed, the algorithm sets a cutoff $\tau_2(c_{2_i})$. Applicants who clear this cutoff receive an offer from their second choice, while those who do not receive a pending offer.

The allocation of 1st-round offers from this algorithm then depends on where r_i lies in comparison to these three cutoffs and is summarized by the following matching function:

$$\mu(i) = \begin{cases} 0 & \text{if } r_i < \tau_0(l_i), \\ c_{1_i} & \text{if } \tau_0(l_i) \leq r_i \text{ and } \tau_1(w_i, c_{1_i}) \leq r_i, \\ c_{2_i} & \text{if } \tau_0(l_i) \leq r_i \text{ and } \tau_2(c_{2_i}) \leq r_i < \tau_1(w_i, c_{1_i}), \\ p & \text{if } \tau_0(l_i) \leq r_i \text{ and } r_i < \tau_1(w_i, c_{1_i}) \text{ and } r_i < \tau_2(c_{2_i}). \end{cases} \tag{1}$$

4.2 Research Design

Our primary interest is to use the variation in equation 1 to estimate the causal effects of G_i, which indicates whether applicant i graduates from a COAR school, on Y_i, the applicant's college outcome. Although the COAR assignment mechanism does not randomly allocate G_i, equation 1 provides quasi-experimental variation in 1st-round offers, facilitating an instrumental variable

(IV) strategy to estimate the effects of COAR graduation.

For this IV strategy, equation 1 provides two sets of potential instruments. First, the variation around the cutoff τ_0 can be used in a standard fuzzy RDD, as applicants who clear this cutoff receive a 1st-round offer to join any COAR school versus a traditional public school, represented by the variable $D_i = \mathbf{1}(r_i \geq \tau_0(l_i))$. The second set of instruments comes from the allocation of school-specific offers D_{is} for $s \in COAR$, comparing applicants around the three cutoffs: τ_0, τ_1, and τ_2. The variation around τ_1 generally determines 1st- versus 2nd-choice offers, while the variation around τ_2 distinguishes between 2nd-choice and pending offers.

The single-offer model is a standard RDD, which enables us to present the main results graphically. In contrast, the multiple-offers model enhances the precision of the estimates compared to a single-offer fuzzy RDD. The over-identification test in the multiple-offers model also helps detect heterogeneity across COAR schools. This model also allows us to adapt the empirical test from Angrist et al. (2017) to assess bias in school value-added models on college outcomes for all secondary schools in Peru, a validation exercise we perform in Section 5.2.

The IV models using 1st-round offers as instruments must address two potential sources of selection bias. First, offers depend on r_i, the admission score, which is a non-lottery tie-breaker and not randomly assigned. Following standard RDD practices, restricting the sample to observations within a bandwidth δ around the admission cutoffs and flexibly controlling for the running variable eliminates this bias.

The second source derives from the first-round offers depending on an applicant's type, θ_i. For instance, the cutoffs an applicant faces are a function of their region of origin and preferences. In principle, full non-parametric conditioning on applicants' type, θ_i, would eliminate such a source of selection bias. For example, the single-offer model, which only uses the variation around cutoffs $\tau_0(l_i)$ can eliminate such bias by non-parametric conditioning on applicants' region l_i, as τ_0 is only a function of this variable.

However, in a design that uses all the variation in the assignment mechanism as the multiple-offers model, full non-parametric conditioning on applicants' type requires conditioning on the combination of region l_i and preferences c_{1_i} and c_{2_i}. While this would remove the bias, it's impractical when only a few observations share the same type, resulting in small sample sizes within each cell. Abdulkadiroğlu et al. (2017a) suggest a solution by conditioning on the propensity score of receiving a school offer for each type rather than full non-parametric conditioning, similar to other stratified randomized research designs (Rosenbaum and Rubin, 1983).

In our design, we follow Abdulkadiroğlu et al. (2017b) and Abdulkadiroğlu et al. (2022), who characterize the local propensity score in the Serial Dictatorship (SD) and Deferred Acceptance (DA) school assignment mechanisms with non-lottery tie-breakers, and extend this analysis to the COAR assignment mechanism. Similar to DA, the variation in the COAR mechanism maps applicants' preferences and priorities into conditional probabilities of quasi-random assignment at each school, creating a school-specific propensity score. Conditioning on the propensity score of the COAR mechanism eliminates the selection bias that stems from the association between the applicant's type and potential outcomes.

The vector of local propensity scores for applicant i, denoted by $\pi_{s,i}$ for $s \in COAR$, is determined by the three cutoffs in equation 1 and the size of the bandwidth δ_j for $j \in \{0,1,2\}$ around each cutoff. While a detailed characterization of the propensity score vector is provided in Appendix C.2, we give a brief explanation here.

By the law of total probability, the propensity score of receiving an offer from each school s is equal to the conditional propensity score on a COAR offer D_i times the probability of a COAR offer, which we denote by π_i:

$$\pi_{s,i} = \tilde{\pi}_{s,i} \times \pi_i, \tag{2}$$

with $\tilde{\pi}_{s,i} = \mathbb{E}[D_{s,i} = 1|\theta_i = \theta, D_i = 1]$. As shown by Abdulkadiroğlu et al. (2022), the local propensity score π_i takes three values when $\delta_0 \to 0$: 0 if $r_i < \tau_0 - \delta_0$, 1 if $r_i > \tau_0 + \delta_0$ and 0.5 if $|r_i - \delta_0| \leq \tau_0$. The intuition behind this result is that as the bandwidth shrinks to 0, offers are uniformly distributed within the bandwidth.

We then characterize $\tilde{\pi}_{s,i}$ when $\delta_1 \to 0$ and $\delta_2 \to 0$. For applicants who do not rank school s ($c_{1_i} \neq s$ and $c_{2_i} \neq s$), we know that $\tilde{\pi}_{s,i}$ equals 0. For applicants who rank school s, this conditional local propensity score would depend on the region where their score r_i lies in comparison to τ_1 and τ_2. Appendix Figure C.1 illustrates this conditional propensity score for the 1st-choice, the 2nd-choice, and a pending offer.

In general, applicants within each bandwidth have a uniform score distribution as the bandwidths shrink to 0. Since 1st-choice offers are processed first, applicants within the τ_1-bandwidth have a conditional propensity score $\tilde{\pi}_{c_{1_i},i}$ of 0.5 for receiving an offer from their first choice. The remaining local propensity score, which should sum up to 1 (as we condition on $D_i = 1$), depends on their score relative to τ_2. If the score is above the τ_2-bandwidth ($r_i > \tau_2 + \delta_2$), then $\tilde{\pi}_{c_{2_i},i} = 0.5$; if they don't get an offer from their 1st choice, they receive an offer from their second choice, and this is uniformly randomized within the τ_1-bandwidth. Conversely, if their score falls below the τ_2-bandwidth ($r_i < \tau_2 - \delta_2$), their counterfactual option is a pending offer, with $\tilde{\pi}_{p,i} = 0.5$. If they lie within both the τ1- and the τ_2-bandwidths, then half of the applicants rejected by the 1st choice receive an offer from their second choice ($\tilde{\pi}_{c_{2_i},i} = 0.25$) and the other half a pending offer ($\tilde{\pi}_{p,i} = 0.25$).

4.3 Empirical Application

We estimate COAR graduation effects with the *COAR analysis sample*, which includes all applicants to the COAR Network between 2015 and 2017, for whom we observe all college applications, admissions, and enrollment between 2017 and 2022. We next describe our estimating equations for the two IV models.

Single-offer model: The single-offer model corresponds to a regular fuzzy RDD as described by the following system of equations:

$$Y_{ilt} = \alpha_0 + \beta G_{ilt} + \psi_{lt} + f(r_{ilt} - \tau_0(l_i, t), D_{ilt}) + \varepsilon_{ilt} \tag{3a}$$

$$G_{ilt} = \alpha_1 + \gamma D_{ilt} + \psi_{lt} + g(r_{ilt} - \tau_0(l_i, t), D_{ilt}) + \nu_{ilt}, \tag{3b}$$

where Y_{ilt} is the outcome variable of student i applying from region l in cohort t, and the variable G_{ilt} is a dummy variable equal to one when applicant i graduates from the COAR Network and zero otherwise. Equation 3a is the second stage of the model with a parameter of interest β, the causal effect of graduating from a COAR school on outcome Y_{ilt}.

Equation 3b is the first stage of the model with a parameter of interest is γ: the effect of D_{ilt}, a binary variable indicating whether the applicant clears the general admission region-specific cutoff, on COAR graduation.

$$D_{ilt} = \begin{cases} 1 & \text{if } r_{ilt} \geq \tau_0(l_i, t) \\ 0 & \text{otherwise,} \end{cases}$$

where r_{ilt} is the composite score of the applicant, and $\tau_0(l_i, t)$ is the score associated with the threshold of the general regional-specific quota for cohort t.

The model in equations 3a and 3b control for a region-by-cohort fixed ψ_{lt} effect and a quadratic function of the running variable $f(r_{ilt} - \tau_{lt}, D_{ilt})$ specific to each region-cohort with different coefficients below and above the threshold:

$$\begin{aligned} f(r_{ilt} - \tau_0(l_i, t), D_{ilt}) \quad &= \quad a_{lt}(r_{ilt} - \tau_0(l_i, t)) + b_{lt}(r_{ilt} - \tau_0(l_i, t))^2 + \\ & \quad\quad c_{lt}D_{ilt}(r_{ilt} - \tau_0(l_i, t)) + d_{lt}D_{ilt}(r_{ilt} - \tau_0(l_i, t))^2. \end{aligned}$$

The first-stage equation includes an analogous polynomial function, $g(r_{ilt} - \tau_0(l_i, t), D_{ilt})$. Finally, ε_{ilt} and ν_{ilt} are the error terms of the second and first stages.

We follow the standard practices on RDDs and limit the sample to applicants within a bandwidth around the general cutoffs. We calculate optimal bandwidths following Imbens and Kalyanaraman (2012) and specific to general outcomes of college enrollment, applications, and admissions. We also validate the single-offer fuzzy RDD with standard tests. Appendix Table A.1 reports balance tests on the individual components of the admission test, sociodemographic variables, baseline test scores, and sending school characteristics. In general, we find evidence that validates our design as the applicants on either side of the admission cutoffs are statistically similar. We also present the manipulation test (Cattaneo et al., 2018) in Appendix Figure A.4, finding no evidence of bunching around the admissions threshold.

Multiple-offers model: Our second empirical strategy leverages all the variation from the assignment in a multiple-offers strategy, where the set of school-specific offers is used as instruments for COAR graduation. The following set of equations describes this model:

$$Y_{ilt} = \alpha_0 + \beta G_{ilt} + \sum_{s \in COAR} \rho_s \pi_{s,ilt} + \psi_{lt} + f(r_{ilt} - \tau_0(l_i, t), D_{ilt}) + \varepsilon_{ilt} \tag{4a}$$

$$G_{ilt} = \alpha_1 + \sum_{s \in COAR} (\gamma_s D_{s,ilt} + \varrho_s \pi_{s,ilt}) + \psi_{lt} + g(r_{ilt} - \tau_0(l_i, t), D_{ilt}) + \nu_{ilt}, \tag{4b}$$

where $D_{s,ilt}$ is a dummy variable indicating whether applicant i receives a first-round offer from school s in the COAR Network. The first main change between the model described by equations 4a and 4b vs. equations 3a and 3b is the fact that now the first stage considers the impact γ_s on COAR graduation of each school-specific offer. The set of schools $s \in COAR$ includes the 25 schools in the Network and a "pending" first-round offer dummy. The controls in equations 4a and 4b include the region-cohort fixed effects and the running variable quadratic polynomials as in equations 3a and 3b. In addition to these covariates, we control for the vector of school-specific propensity scores of receiving an offer from each school s, denoted by $\pi_{s,ilt}$, including the propensity score of receiving a pending offer.

The payoff to the propensity-score conditioning over full non-parametric conditioning on applicants' types is a higher statistical power as the latter would reduce the degrees of freedom by eliminating many students from the analysis sample. For instance, in our data, a model with full applicant-type conditioning would imply controlling for around 551 different risk sets in our estimations. By contrast, the model controlling for the propensity score can achieve balance without the loss in the degrees of freedom.

We validate the multiple-offer fuzzy RD design by showing balance tests of school-specific offers on students' baseline characteristics. Column 6 of Table A.1 reports the p-value of a joint test that all estimates of γ_2 for $s \in COAR$ are equal to zero after controlling for the vector of propensity scores. Overall, we do not reject this null hypothesis at conventional significance levels for almost all characteristics at baseline, validating this design.

4.4 Main Results

4.4.1 First Stage

We first report the first stage of the single- and multiple-offers model on COAR graduation. For several reasons, the 1st-round offers are not a perfect predictor of COAR graduation. First, applicants may prefer to enroll in a traditional public school than in the offered COAR school. The effects of first-round offers on COAR graduation can also be weaker than on enrollment due to COAR dropouts or transfers during the three years of high school. Columns 1 to 3 in Table 2 (with analogous RD plots in Panels A to C of Figure 2) report the first stage, the estimates of parameter γ in equation 3b for various first-stage outcomes.

Column 1 and Panel A report the effect of clearing the admission cutoff on the likelihood of receiving a first-round offer from a COAR school according to the government files. The point estimate is 100 p.p., confirming that our replication of the algorithm has perfect predictive power on the first-round offers in the admin data. Columns 2 (Panel B of the figure) and Column 3 (Panel C) report the effects of clearing the general admission cutoff on 3rd-grade COAR enrollment and COAR graduation, showing a positive impact of 52.2 p.p. (s.e. 2.0 p.p.) on enrollment, with a slightly smaller estimate of 46.9 p.p. (s.e. 2.1 p.p.) on graduation. The similarity between these two point estimates shows that dropout is uncommon once students enroll in a COAR school.

Figure 3 depicts the first stage of the multiple-offers model, the estimates of school-specific COAR offers effects, parameters γ_s in equation 4b, on the likelihood of graduating from the COAR network. Out of 26 COAR offers, 25 are statistically significant on COAR graduation. Among the offers with a statistically significant effect, 23 COAR offers have an impact of at least 50 percentage points on graduation, ranging from 50 to 90 percentage points.

We next report the first-stage estimates on the average school graduates characteristics.[4] Columns 4 to 6 in Table 2 report the 2SLS estimates of COAR graduation on average school graduates characteristics for the single-offer model, with Panels D to F in Figure 2 showing the analogous RD plots.

[4] As these measures come from standardized tests in 2nd-grade in secondary school that the government started to implement in 2015, this data is not available for the 2015 cohort, and the sample of analysis only includes the 2016-17 cohorts.

On average, applicants marginally admitted to the COAR Network experience a sharp difference in average graduates characteristics. The 2SLS estimates in the single-offer model reveal an increase of 1.65σ and 1.37σ in average graduates math and reading scores at baseline (Columns 4 and 5 in Table 2). There is also a significant increase of 0.24σ in their average socioeconomic index (Column 6 in Table 2), but this difference is relatively small compared to the changes in test scores. Graduating from the COAR Network affects the average characteristics of graduating peers, as documented for elite public schools in other contexts (Abdulkadiroğlu et al., 2014; Dobbie and Fryer, 2014; Lucas and Mbiti, 2014).

4.4.2 2SLS Effects on College Outcomes

We next explore COAR graduation effects on college outcomes. Table 3 reports estimates of the second stage of the single-offer (equation 3a) and multiple-offers (equation 4a) models on college enrollment. Column 1 reports general enrollment, and columns 2-6 by type of university. Panels A and B display the 2SLS estimates in the single- and multiple-offers models, respectively.

Graduating from the COAR Network has a statistically significant effect on college enrollment. The single-offer model estimates show that graduating from the COAR network increases enrollment at any university by 11.9 p.p. (s.e. 5.4 p.p.), an increase of 17% compared to the control mean. The multiple-offers model estimates are relatively similar to those from the single-offer model, showing an effect of 9.1 p.p. (s.e. 3.0 p.p.). The over-identification test does not reject the null of homogeneous COAR effects.

Private university enrollment drives the positive impact on overall college enrollment. The single-offer model estimates a 19.6 p.p. increase (s.e. 6.1 p.p.) in private enrollment, contrasting with a -4.6 p.p. effect (s.e. 5.9 p.p.) on public enrollment. The 2SLS estimates using multiple instruments are similar, showing COAR graduation boosts private university enrollment by 17.4 p.p. (s.e. 3.5 p.p.) and significantly decreases public enrollment by -7.9 p.p. (s.e. 3.5 p.p.).

The estimates indicate larger effects for top private universities compared to top public ones. In the single-offer model, the 2SLS estimates show a significant increase of 15.8 percentage points (s.e. 3.8 p.p.) in enrollment at top private universities, approximately a 154% increase from the control mean. In contrast, COAR graduation has an insignificant effect on enrollment at top public universities, with an estimate of only 0.1 percentage points (s.e. 3.3 p.p.). The multiple-offers model yields smaller effects but a similar pattern: a 9.4 percentage point increase (s.e. 2.2 p.p.) for top private universities, and a non-significant effect of -1.7 percentage points (s.e. 1.9 p.p.) for top public universities. The over-identification test marginally rejects the hypothesis of homogeneous effects, suggesting heterogeneous impacts on enrollment at top public universities.

Table 4 reports effects on applications and admissions. Columns 1-2 present the 2SLS estimates for applications and admissions at private universities, while columns 4-5 do the same for public universities. For comparison, columns 3 and 6 replicate the 2SLS enrollment estimates from Table 3. Section I covers results for all universities, and Section II focuses on the top-10 universities. Within each section, Panels A and B display the 2SLS estimates using the single- and multiple-offers models, respectively.

Both the single- and multiple-offers models yield similar conclusions regarding the impact of COAR graduation on applications and admissions to private and public universities. The findings show that COAR graduation significantly increases the likelihood of applying to private universities by 27.7 to 35.7 percentage points (s.e. 3.6-6.5 p.p.), with no effect on applications to public universities. The admission effects reveal that COAR graduates have an admission rate to private universities of 19.7 to 22.4 percentage points higher (s.e. 3.4-6.0 p.p.) than that of marginally rejected COAR applicants, explaining the changes in college enrollment.

The results in Section II of Table 4 reveal a similar pattern for top-10 universities. COAR graduates apply more frequently, have higher admission rates, and enroll more at top-10 private institutions, with smaller or no effects observed for top-10 public institutions. The multiple-offers model rejects the over-identification test for applications and admissions to top-10 universities, both public and private, indicating heterogeneity across COAR schools on these outcomes. Notably, while COAR graduates are more likely to apply to top-10 public universities by 10.6 to 14.2 p.p. (s.e. 3.0-5.6 p.p.), this increase in application rates does not result in higher admissions or enrollment (Section II, columns 5 and 6).

4.4.3 2SLS Effects on Type of Admission

A key advantage of our analysis is that we can distinguish COAR effects by application and admission mode. Despite not being a conclusive test, as many criteria for extraordinary admissions explicitly benefit some schools, COAR effects on extraordinary admissions would suggest that private universities use COAR graduation as a signal of applicants' talent. Table 5 reports COAR effects by admission mode for private universities. The first two columns report the estimates on application and admission for exam admissions, columns 3 and 4 for extraordinary admissions, and the last two for preparatory academic admissions.

COAR has significant effects on both exam-based (columns 1-2) and extraordinary (columns 3-4) applications and admissions at private universities, with no impact on preparatory academies (columns 5-6). In all private universities (Section I), the effects on extraordinary admissions are larger than those on exam admissions. For the top 10 universities (Section II), while the effects are slightly smaller, they remain similar in magnitude. This implies that extraordinary admissions account for approximately 47% to 76% of the total effect on admissions. In contrast, estimates for public universities in Appendix Table A.2 are non-significant on applications and admissions across all three admission modes. While COAR graduation boosts applications to top-10 public universities, the higher application rates do not lead to higher admission.

The results suggest that COAR graduation increases applications and admissions at private institutions, with top-10 universities driving a significant proportion of the overall effect. The following section explores the mechanisms underlying these positive effects.

4.5 Mechanisms

4.5.1 Human Capital Gains

One possible explanation for the effects on college outcomes is that COAR leads to gains in human capital. However, similar to the evidence on elite schools in other contexts (Abdulkadiroğlu et al., 2014; Lucas and Mbiti, 2014; Dobbie and Fryer, 2014; Angrist et al., 2023), two additional pieces of empirical evidence indicate that the impact of COAR on learning and non-cognitive skills is, at best, inconclusive.

First, an independent evaluation commissioned by the Ministry of Education found no evidence that COAR schools improve learning or non-cognitive skills (Hatrick and Paniagua, 2021). Appendix Table A.3 indicates precise zero effects on math and reading scores. The estimates for non-cognitive skills are less precise and vary widely, showing some positive effects on grit but negative impacts on school attitude and leadership—none of which are statistically significant. Overall, these results do not support human capital gains as a relevant mechanism.

As a second exercise, we examine whether COAR affects performance on university-specific admission exams, accounting for selection bias. As COAR graduation might influence the choice of institutions and admission modes, leading to differential attrition in observing an exam score, we focus on universities with minimal evidence of this issue. Panel A of Appendix Figure A.5 shows the effect of clearing the admission cutoff on the likelihood of observing an exam score for each of the 110 universities. Panel B provides the p-values from the joint significance test for the multiple-offers model. We estimate COAR effects on exam performance, excluding universities with statistically significant reduced-form effects on the likelihood of observing an exam score.

Table 6 presents reduced-form and 2SLS COAR graduation effects on the likelihood of having an exam score and exam performance. All models include university and application period fixed effects, with exam scores standardized at the university-major level. Since students can apply to multiple universities or programs, standard errors are clustered at the student level. Columns 1 to 3 show estimates excluding universities with statistically significant attrition effects at the 5% level, while columns 4 to 6 exclude those at the 10% level, for both the single-offer (Panel A) and multiple-offers models (Panel B). For reference, Appendix Table A.5 provides the same estimates for all universities.

Overall, the results indicate that COAR graduation has little impact on admissions exam performance. Across all university sample restrictions, the single-offer model yields non-significant estimates for 1st-round offers on exam scores, ranging from -0.003 to 0.011σ (s.e. 0.048-0.049), translating to COAR graduation effects between -0.006 and 0.023σ (s.e. 0.113-0.118). The multiple-offers model in Panel B provides even more precise 2SLS estimates, with effects between 0.006 and 0.015σ (s.e. 0.083). These estimates, including those from the balanced attrition sample, are similar to the results for all universities shown in Appendix Table A.5. The precision and size of these effects are comparable to findings from other studies that report negligible impacts of elite schools on test score outcomes (Abdulkadiroğlu et al., 2014; Barrow et al., 2020; Angrist et al., 2023).

In summary, the evidence from Hatrick and Paniagua (2021) and the estimates of COAR effects on admission exam scores indicate a negligible impact of COAR schools on learning, suggesting that learning gains are unlikely to explain the main effects on college outcomes.

4.5.2 Signaling

The second mechanism we explore is signaling: whether COAR effects on college outcomes stem from universities using signals of students' abilities, such as the school they graduated from. While some previous evidence, like the estimates on extraordinary admissions, hints at this mechanism, aggregate effects on admissions involve both student application choices and university policies. To isolate the signaling effect, we conduct two additional exercises. First, we estimate COAR effects on eligibility for extraordinary admissions, focusing solely on university admission policies. Second, we examine the impact of a second signal among COAR graduates: the effect of marginally obtaining the IB diploma.

The first exercise examines eligibility for extraordinary admissions. Universities may infer COAR graduates have higher skills, given that the network typically has graduates with higher baseline achievement than comparable schools (columns 4-5 of Table 2). Additionally, COAR schools are recognized by the media and public as elite institutions for talented low-income students. For instance, El Comercio, a major Peruvian outlet, describes the COAR Network as offering 'high-quality education to the brightest students' who must pass a stringent examination to enroll (El Comercio, 2014). Such a high reputation could potentially influence university admission policies.

We use two methods to assess eligibility for extraordinary admissions. The first method, an empirical approach, considers a school eligible if at least one graduate applies through specific types of extraordinary admissions, such as a list of preferred institutions or the IB diploma. The second method evaluates eligibility based on the government ranking of the top 32 universities. We review each university's admission policies and classify a school as eligible if it is explicitly listed in the admission documents. Appendix Figure A.1 provides an example. For IB admissions, we consider whether the school offers the IB and if the university has a special admission mode for IB applicants.

Table 7 presents the single- (Panels A) and multiple-offers (Panels B) models on the number of universities where COAR graduates are eligible for extraordinary admissions via preferred schools using the empirical method. Column 1 shows results for all universities, while columns 4 and 7 focus on private and public universities, respectively, with Section I covering all universities and Section II the top 10. The results indicate a significant increase in the number of universities COAR graduates can apply to compared to non-COAR graduates. The single-offer model shows an increase of 28.2 universities (s.e. 0.106), including 9.5 private and 18.7 public universities. Among these, 2.16 private and 2.00 public universities are in the top 10. The multiple-offer models yield even larger estimates, with over-identification tests indicating considerable heterogeneity among COAR schools in this eligibility. Appendix Table A.6 compares the empirical method with admission policy documentation for top-10 and top-32 universities, showing similar results.

Interestingly, while most effects on enrollment (Table 3) are at top private universities, the eligibility results show larger increases for public institutions. The documentation used to construct the eligibility measures reveals that this is mainly due to some public universities creating special admission modes specifically for COAR graduates, though with limited slots.[5]

The International Baccalaureate Diploma

[5]For example, one public university offered 278 slots to COAR graduates or top-2 class students from any school. Applicants took a simplified admission exam, with slots assigned strictly by merit. Of the 478 applicants, 44 were COAR graduates, but only 12 secured a slot.

We also examine COAR effects on extraordinary admissions eligibility through the IB diploma. The IB program is a two-year curriculum managed by a nonprofit in Switzerland, recognized by many universities worldwide as a qualification for college entry. Schools offering the IB must undergo an authorization process and pay a fee of USD 12,233 in 2023. In Peru, the Ministry of Education has managed that all COAR schools offer the IB program, which was mandatory for all COAR graduates until 2017. Only COAR schools, schools for military children, and elite private schools in Peru offer the IB program.

We find evidence that universities also use the IB diploma as a signal of applicants' ability. Columns 2, 5, and 8 of Table 7 show the estimated effects of COAR graduation on the number of universities offering IB extraordinary admission. On average, COAR graduates can apply to about 21.35 additional universities (s.e. 0.109) due to the IB, including 17.35 private and 4 public institutions. Among these, 7 are in the top 10, comprising 5 private and 2 public universities.

Since many COAR students do not receive the IB diploma, columns 3, 6, and 9 adjust for whether a COAR graduate obtained the IB. This analysis is limited to the 2015-16 cohorts as the IB data is unavailable for the 2017 cohort. The RD estimates show significant effects even when accounting for IB attainment, although they are smaller than in earlier columns. Only about 30% of COAR graduates around admission cutoffs receive the IB diploma. Despite this, the results indicate a significant and large effect on extraordinary admissions eligibility via the IB, especially given that marginal applicants are less likely to obtain the diploma than other COAR students.

To further explore the signaling mechanism, our second exercise estimates the effect of marginally obtaining the IB diploma among COAR graduates. Students need at least 24 points across six subjects to receive the diploma, with scores based on external exams. We compare students who scored 23 points, just missing the diploma, with those who scored 24 points, barely qualifying. Since these groups are likely similar in academic and non-academic abilities, the critical difference is receiving the diploma.

Our strategy considers a fuzzy design as obtaining the diploma involves additional requirements, like completing the Creativity, Activity, and Service (CAS) component. The following system of equations describes the first and second stages of this research design:

$$Y_{ist} = \alpha_0 + \beta IB_{ist} + \psi_{st} + \varepsilon_{ist} \quad (5a)$$

$$IB_{ist} = \alpha_1 + \delta Z_{ist} + \psi_{st} + \nu_{ist} \quad (5b)$$

where Y_{ist} represents the outcome for student i from school s and cohort t. The variable IB_{irt} is a dummy equal to one if the student receives the IB diploma and zero otherwise. The variable Z_{ist} indicates whether a student scores 24 in the IB program instead of 23. Our estimations include school-by-cohort fixed effects ψ_{st}. We also provide randomization inference p-values for the reduced form of this model, following Cattaneo et al. (2020).

We first validate this empirical design by showing that scoring 24 vs. 23 points does not predict academic or non-academic skills. Appendix Table A.4 shows the RF estimates of equations 5a and 5b. The balance variables include math and reading performance, self-reported psychological measures such as personality traits and stress, and social network metrics like the number of friends, study partners, and centrality. The estimates confirm that the two groups are similar across these dimensions, supporting the validity of our design. Figure 5 shows the design has a strong first stage. Achieving a score of 24 versus 23 points leads to a 74 p.p. increase (s.e. 2.9 p.p.) in the likelihood of obtaining the IB diploma.

Table 8 shows the reduced-form and 2SLS estimates of the IB diploma's impact on applications, admissions, and enrollment at top-10 universities, with Appendix Table A.7 providing results for all universities. The IB signal primarily affects admission and enrollment at the most selective private institutions. Section I presents estimates for private universities and Section II for public ones. Columns 1 and 2 show results on applications and admissions via exams, columns 3 and 4 on extraordinary admissions, columns 5 and 6 on preparatory academies, and column 7 on enrollment.

The findings support the idea that the IB signals applicants' skills, with top private universities valuing these signals more in their admissions processes than public universities. Column 7 shows that obtaining the IB diploma increases the probability of enrolling in a top-10 private university by 17.3 p.p. (s.e. 4.7 p.p.), which is about a 138% increase relative to the control mean. Additionally, column 4 indicates that this positive effect on enrollment is primarily driven by extraordinary admissions. In contrast, the IB diploma has no statistically significant impact on admission or enrollment rates at public universities.

In summary, COAR graduates are more eligible for extraordinary admissions and benefit from additional signals like the IB diploma. These findings support signaling as a key mechanism behind the observed COAR effects on college enrollment, contrasting with the inconclusive evidence on human capital.

4.5.3 Other Mechanisms: Aspirations and Information

We end this section by considering two mechanisms that might also explain the main effects: differences in students' aspirations and information about college opportunities. While these mechanisms do not rule out signaling, they could partially explain some previous findings.

We first explore the role of aspirations (Genicot and Ray, 2017). Imperfect information in the college market affects both universities and students—universities lack information on student abilities, and students are not fully aware of their own skills. These information gaps are more pronounced in the absence of standardized tests. In this context, an offer from a COAR school, known for targeting the most talented students, has two signaling effects: it signals the student's abilities to the market but also informs the student and their family of their potential.

Two pieces of evidence support the aspirations mechanism. First, COAR graduation affects exam admissions at private institutions, likely driven by students' application decisions. The increase in unconditional exam admissions (column 2, Table 5) appears to result from higher application rates (column 1 of the same table). Since Table 6 shows no significant differences in admission exam performance after accounting for selection bias, higher aspirations may explain the admissions effect by motivating students to apply more to college.

We also cannot entirely rule out differences in information about college opportunities as another potential channel (Hoxby and Turner, 2015; Dynarski et al., 2021). While aspirations may drive application decisions, COAR schools could also provide better information about college opportunities, contributing to the observed effects. Despite inconclusive evidence on COAR schools' effectiveness in improving learning, they may have access to better information on university admissions. Although our data can't distinguish between the aspirations and information mechanisms, higher application rates appear to drive the impact on exam admissions, with both mechanisms potentially shaping these decisions.

5 Other Secondary Schools

We next explore whether the previous findings extend to other schools in Peru, specifically examining if school effects on learning outcomes or reputation predict school effects on college outcomes. We estimate school value-added (SVA) models for both learning and college outcomes. First, we introduce a general value-added model framework, followed by the estimation and validation tests. We then explore the relationship between school effects on college outcomes, value-added to learning, and school reputation.

5.1 Estimation of School Value-Added Models

As a general framework, let $\mathcal{I}$ represent the population of students indexed by i, enrolled in or graduating from high school j. Let Y_{ij} be the potential outcome for student i at school j. Under a constant-effects model,[6] the potential outcome for student i is the sum of the school's mean outcome, μ_j, and a composite measure of all other individual characteristics, such as family background, motivation, ability, and aspirations, captured by a_i:

$$Y_{ij} = \mu_j + a_i. \tag{6}$$

Let D_{ij} indicate student i enrollment or graduation from school j. Then, the observed outcome for student i can be written as:

$$Y_i = Y_{i0} + \sum_{j=1}^{J} (Y_{ij} - Y_{i0}) D_{ij}, \tag{7}$$

where the difference, $Y_{ij} - Y_{i0}$,represents the value-added of school j for student i relative to a reference school. Under a constant-effects model, this value-added is the same for all students. Substituting equation 6 into equation 7, we obtain:

$$Y_i = \mu_0 + \sum_{j=1}^{J} \beta_j D_{ij} + a_i \tag{8}$$

where μ_0 is the average outcome for students at the reference school, β_j is the value-added of school j relative to the reference school, and a_i represents the composite measure of students' individual characteristics.

As particular school attendance or graduation is partially driven by a_i, an OLS estimation of 8 will render inconsistent estimates of β_j. Hence, we follow the literature on value-added models

[6] We focus on a constant-effects model since our main hypothesis is that universities use the graduating secondary school to infer applicants' characteristics.

by using covariates to mitigate selection bias. In particular, we assume that the term a_i has the following functional form:

$$a_i = X_i'\Gamma + \varepsilon_i \tag{9}$$

where X_i is a vector of observable characteristics, and the remaining determinants of Y_i are unobserved factors captured by the term ε_i. Substituting 9 into 8, we have that:

$$Y_i = \mu_0 + \sum_{j=1}^{J} \beta_j D_{ij} + X_i'\Gamma + \varepsilon_i. \tag{10}$$

Following the value-added literature (Chetty et al., 2014b; Angrist et al., 2017; Abdulkadiroğlu et al., 2020), we estimate an empirical version of the model in equation 10. The vector $\beta_j{}_{j=1}^{J}$ represents the value-added of school j relative to a reference school, which are the parameters of interest. Our SVA model estimates correspond to the secondary school fixed effects from the empirical version of equation 10.

We control for a rich set of individual and family background covariates. In particular, our models control for individual characteristics, including students' gender, age, preschool attendance, and grade retention. The models also account for socioeconomic conditions by including a cubic polynomial of the socioeconomic index and control for household assets, dwelling conditions, and parental education levels. Given the importance of baseline scores for controlling selection (Chetty et al., 2014a), we also include cubic polynomials of math and reading scores from primary and secondary school tests for college outcomes, as well as GPA and grades from the previous year. Additionally, we control for whether the student is a COAR applicant, with this effect varying by region. Appendix Table A.8 lists the set of covariates each outcome.

We estimate SVA on college outcomes using equation 10, focusing on college enrollment and admissions by university type and admission mode. The analysis includes all students who took the 2nd-grade high school standardized test in 2015 or 2016, referred to as the *All Schools Sample* in Section 3. The relevant secondary school is defined as the one a student attends three years after taking the test, typically their graduating school. We restrict the sample to schools with at least ten students per cohort to ensure precise SVA estimates.

We estimate SVA on learning outcomes using equation 10 on test scores in 2nd grade of secondary school. Since our models flexibly control for 2nd-grade primary school test scores, the main outcome is learning gains between these periods. Most secondary schools in Peru offer all five years of secondary education, but COAR schools only operate for the last three years, preventing us from including them in this analysis. The sample is limited to students who took the secondary school test in 2015 and 2016, which matches two of the three COAR cohorts. Our results are similar for all test-takers from 2015 to 2019. An implicit assumption is that SVA to learning in the first two grades is similar in the last three.

As school-specific effects are estimated with noise, we follow Chetty et al. (2014a) and Beuermann et al. (2022), and rely on the correlations between school effects across years to identify the persistent school effects over time on college and learning outcomes. As we only have two cohorts of students, we separately estimate the school value-added for each cohort and then calculate the value-added of school j as the predicted value of an OLS regression of the SVA for the 2016 cohort on the SVA for the 2015 cohort.

We do not apply the Empirical Bayes (EB) shrinkage method to SVA estimates on college outcomes for two reasons, following Angrist et al. (2022). First, we focus on specific schools rather than averages, and second, SVA on college outcomes serves as the dependent variable in our analysis, not as a regressor. Instead, we weigh all our exercises by the number of students, as SVA estimates are more precise for larger schools. In contrast, since we use SVA on learning as a regressor, we estimate the hyperparameters of the parametric normal model in (Gilraine et al., 2020) by maximum likelihood and use the shrunk SVA on learning in our analysis.

5.2 Testing for Bias in School Value-Added Models

We present two validation tests as the school value-added estimates of equation 10 rely on a selection-on-observables assumption. The first one adapts the lottery-based test for bias in non-experimental estimators of school effectiveness proposed by Angrist et al. (2017) to the multiple-offers RDD variation from the COAR mechanism. The second one tests for selection on unobservables following Jackson et al. (2020).

5.2.1 COAR Multiple-Offers Model

While the estimates of school value-added from equation 10 come from observational data and can rely on strong assumptions of students' sorting across schools, the school-specific offers assignment from the COAR mechanism provides plausibly exogenous variation in school enrollment which allows to test the accuracy of such SVA estimates.

The empirical test relies on the idea that if school value-added estimates are accurate, the quasi-experimental variation from the first-round offers should have perfect predictive power on COAR schools' SVA. The test is implemented by estimating the following 2SLS system:

$$Y_{ijlt} = \alpha_0 + \phi\widehat{SVA}_j + \sum_{s \in COAR} \rho_s \pi_{s,ilt} + \psi_{lt} + f(r_{ilt} - \tau_0(l_i,t), D_{ilt}) + \varepsilon_{ilt} \quad (11a)$$

$$\widehat{SVA}_j = \alpha_1 + \sum_{s \in COAR} (\gamma_s D_{s,ilt} + \varrho_s \pi_{s,ilt}) + \psi_{lt} + g(r_{ilt} - \tau_0(l_i,t), D_{ilt}) + \nu_{ilt}, \quad (11b)$$

where 11b is the first-stage equation and 11a is the second stage. $\widehat{SVA}j$ represents the non-experimental estimate of the SVA for COAR school j from equation 10, with other variables defined as in equations 4a and 4b. The first-stage coefficients γs indicate the predicted effects of each COAR school offer on the non-experimental SVA. These coefficients are non-zero if COAR value-added estimates differ from those of counterfactual schools, as first-round offers shift student graduation from traditional public schools to COAR schools.

Angrist et al. (2017) show that the "forecast coefficient" ϕ in equation 11a should equal 1 if the SVA estimates accurately predict the effects of school-specific offers in the multiple-offers model. The over-identification test of equations 11a and 11b further measures whether the estimator has the same predictive validity across the set of COAR offers. The combination of both restrictions can be viewed as a Hausman-type test comparing the fuzzy multiple-offers RDD estimates to the OLS value-added estimates from observational data.[7]

[7] An implication of the constant effects model of school value-added is that the local average treatment effect estimated by our 2SLS strategy equals the average treatment effect.

Table 9 reports the 2SLS estimates of equation 11a, indicating that the SVA estimates from equation 10 align with the predicted COAR effects in the multiple-offers model. Column 1 shows the 'forecast' coefficient, with the standard error in column 2. Column 3 reports the p-value for testing if this coefficient equals 1. Columns 4 and 5 display the over-identification test and its p-value, while column 6 provides the first-stage F-statistics.

The estimates in Panel A show that for all universities, the SVA estimates align with the multiple-offers model. The forecast coefficient for any college, private, and public enrollment is close to 1, and the over-identification test is not rejected for any outcome. While estimates for top-10 enrollment are further from one, the formal test does not reject equality. The test shows more reliable forecasts for top-10 private than public enrollment, where COAR offers have a higher predicted value, as indicated by the first-stage F-statistic. Similar conclusions apply to SVA on admissions and admission modes by university type. The test generally supports alignment between the SVA and multiple-offers model for admissions at private universities (Panels B and C). Although the forecast coefficient on exam admissions at top-10 private universities is further from one, the test is reliable for extraordinary admissions, our primary focus, which benefit specific secondary schools and where COAR offers have higher predictive power (first-stage F-stat of 48.96 vs. 23.71).

In contrast, the validation test in Panels B and D shows less alignment between the COAR multiple-offers model and the SVA estimates for public university admissions. Since private universities, where COAR offers have more predictive power, rely more on special admissions to specific high schools, we focus our analysis on them. The forecast coefficient estimates in Table 9 differ from those in Appendix Table A.9, which use 'uncontrolled' school-level averages as SVA measures. For SVA that does not control for covariates, the test rejects the forecast coefficient being equal to 1 for nearly all outcomes except exam admissions.

5.2.2 Testing for Selection on Unobservables

As COAR schools start in the third grade of secondary school, we cannot use the test from equation 11a to validate SVA on learning. Instead, we follow Jackson et al. (2020) to test for selection on unobservables for both learning and college outcomes. Specifically, we estimate the standardized effect of SVA on students' outcomes and test if this estimate changes when controlling for additional unobservable characteristics. We use the following estimating equation:

$$Y_{ijt} = \vartheta_0 + \vartheta_1 \widehat{SVA}_j + \varsigma' X_i + \tau_t + \nu_{ijt}, \tag{12}$$

where Y_{ijt} is the outcome of student i in school j from cohort t, $\widehat{SVA}_j$ is the standardized SVA estimate of school j on outcome Y, X_i is a vector of individual and family background characteristics, τ_t are cohort fixed effects, and ν_{ijt} is an error term. The parameter of interest is ϑ_1, the effect of the standardized SVA of school j on the student outcome.

We validate our SVA measures by testing the robustness of the estimates of ϑ_1 to two alternative models. The first is a 2SLS model that uses the SVA of the nearest school to the family's residential address from the 2017 Census as an instrument for the SVA of student i's school. A difference between the OLS and 2SLS estimates would suggest that families choose schools based on factors other than location, indicating potential bias in our SVA estimates. The second strategy involves comparing students within the same household who attend different schools by estimating equation 12 with household fixed effects, controlling for all unobserved household-level characteristics.

Table 10 reports the estimates of equation 12 for learning and main college outcomes, including enrollment and admissions, while Appendix Table A.10 focuses on admission modes for private and public universities. Column 1 shows the OLS estimate for all students, columns 2 and 4 provide estimates for students with household locations from the 2017 Census and those with children in multiple secondary schools, respectively. Column 3 presents the 2SLS estimate using the SVA of the nearest school, and Column 5 includes household fixed effects. The overall conclusion is that the estimates of ϑ_1 are consistent across all samples and models, suggesting minimal bias from unobservables in the SVA estimates of equation 10.

5.3 SVA on College Outcomes: Reputation vs. Effectiveness

We next examine the link between SVA on college outcomes, school effectiveness (measured by SVA on learning), and reputation (measured by graduates' average characteristics). If college admissions prioritize rewarding schools for enhancing learning, there should be a positive relationship between SVA on college outcomes and SVA on test scores. Conversely, if admissions focus more on a school's prestige or socioeconomic background, then average test scores and the socioeconomic index would better predict SVA on college outcomes.

Since Figure 1 shows a highly non-linear relationship between college admissions and school average characteristics, with larger effects for schools at the top of the socioeconomic index distribution, we estimate a non-parametric model using the 100 percentiles of our variables of interest. We omit the 1st percentile and include dummy variables for the remaining 99 percentiles for three school variables: (i) SVA on learning, measured by school effects on the sum of math and reading test scores, (ii) average graduates' test scores, and (iii) average socioeconomic index.

The following equation describes our estimating model:

$$Y_j = \sum_{q=1}^{100} (\delta_q \mathbf{1}(q_{v,j} = q) + \eta_q \mathbf{1}(q_{a,j} = q) + \psi_q \mathbf{1}(q_{e,j} = q)) + \xi_j, \tag{13}$$

where Y_j is the SVA estimate of school j on the respective college outcome, and $\mathbf{1}(q_{x,j} = q)$ indicates that for variable x school j is in percentile q of the distribution, with v indicating value added, a indicating average test scores, and e indicating average socioeconomic index, and ξ_j representing the error term. The parameters of interest are the vectors $\boldsymbol{\delta}$, $\boldsymbol{\eta}$, and $\boldsymbol{\psi}$ that show the relationship between SVA on college outcomes and each percentile of SVA on learning, average test scores, and average socioeconomic index.

Figure 6 presents the estimates of equation 13 on SVA for college enrollment at private universities, with column 1 showing effects for all private universities and column 2 for top-10 universities. Panel A illustrates the relationship between SVA on test scores and these outcomes using two models: the red dots represent estimates of $\boldsymbol{\delta}$ without additional controls, and the blue dots include controls for average scores and socioeconomic index quantiles. Panels B and C show analogous estimates for $\boldsymbol{\eta}$ and $\boldsymbol{\psi}$, representing the effects of average scores and socioeconomic index percentiles, respectively. The red dots indicate estimates without extra regressors, while the blue dots are models that include all three variables. Figure 7 presents these estimates for public universities.

Figure 6 shows a positive relationship between SVA on college enrollment at private institutions (both overall and top 10) and SVA on learning, but this relationship vanishes after controlling for average scores and socioeconomic index. In the fully saturated model, SVA on learning does not predict school effects on college enrollment at private universities. While Panel B suggests some predictive power for average achievement, the average socioeconomic index has the strongest influence on SVA for enrollment at private universities. The difference between the top percentiles and the 1st percentile of the socioeconomic index is more than double that of average scores for all universities and about 1.5 times for top-10 private universities.

In contrast, Figure 7 indicates that SVA on learning somehow predicts SVA on enrollment at public universities, including top-10 institutions. While the evidence does not conclusively show that higher SVA on test scores increases enrollment at public universities, most differences between SVA percentiles and the 1st percentile are statistically significant, even when including all three regressors. Panel B shows that average scores primarily predict SVA on enrollment at top-10 public universities, while Panel C reveals that higher percentiles of the average socioeconomic index reduce enrollment at public institutions, likely due to students' application preferences. Appendix Figures A.6 and A.7 present similar findings for admissions at private and public universities.

Figure 8 examines this same relationship on extraordinary admissions at private universities. Like enrollment effects, the results show that SVA on learning does not predict extraordinary admissions after controlling for average scores and socioeconomic index. While average scores have some predictive power for admissions, their impact is minor compared to the socioeconomic index. Appendix Figure A.8 illustrates the relationship for exam admissions at private universities, indicating that average scores do predict this admission type. Schools in the top percentiles of the socioeconomic index benefit the most from extraordinary admissions (percentiles 99 and 100), with percentiles 75-98 and 87-98 predicting exam admissions for all private and top-10 private universities, respectively.

Since admissions and enrollment estimates reflect both student preferences and university admission policies, Figure 9 shows the estimates of equation 13 on eligibility for extraordinary admissions, abstracting from student preferences. Column 1 reports estimates for eligibility of IB admissions, while columns 2 and 3 on preferred schools eligibility for top-10 and top-20 private universities.

SVA on learning has little predictive power on eligibility after controlling for average scores and socioeconomic background. Being in the top percentile of SVA on learning predicts eligibility via the IB. Still, the effect is less than half that of being in the top percentile of the average socioeconomic index. Columns 2 and 3 reveal an even more striking result, with SVA on learning showing negative estimates at the top percentiles when including all three regressors. In contrast, while average scores and socioeconomic index have similar effects on eligibility for top-10 universities, the socioeconomic index is more predictive than average scores for top-20 private universities. This result suggests that universities primarily target the average socioeconomic background over average scores for extraordinary admissions, with both factors having more influence than SVA on learning.

5.3.1 Comparison of Eligible Schools for Extraordinary Admissions

We conclude this section by comparing the average characteristics and SVA of schools eligible for extraordinary admissions with three types of schools: (1) schools with comparable SVA on learning, (2) schools with similar average graduates' scores, and (3) COAR schools. Schools are considered comparable in SVA on learning or average test scores if they fall within the same percentiles of these distributions as the schools eligible for extraordinary admissions.

Comparing eligible schools with the first two groups indicates that school value-added on learning and average scores have minimal impact on college access segregation, which is primarily driven by socioeconomic background through extraordinary admissions. In contrast, the comparison with COAR schools shows that, despite inconclusive evidence on their impact on human capital, these schools help talented low-income students close income gaps in college access by providing a way to signal their skills.

Table 11 presents the differences in standardized outcomes at the school level for IB schools (columns 1-4) and schools on the list of preferred schools for top-10 private universities (columns 5-8). Columns 1 and 5 present the standardized mean of each group, while columns 2 and 6 show the difference with schools comparable in SVA on learning. Columns 3 and 7 compare them with similar schools in average graduates' scores, and columns 4 and 8 with COAR schools. The values in columns 2-4 and 6-8 represent the difference between the respective group and the eligible schools for extraordinary admissions. Appendix Table A.11 provides the analogous comparison for schools on top-5 and top-20 private university lists.

The results align with the previous analysis: schools with graduates from higher socioeconomic backgrounds benefit the most from extraordinary admissions, while SVA on learning or average scores play a minimal role in explaining these differences. For instance, schools comparable to IB schools in SVA on learning have lower average scores by 0.28 to 0.39σ, but the difference in SVA on extraordinary admissions at private universities is much larger—1.90σ lower overall and 2.47σ lower for top-10 private universities. Similar schools in average scores show a similar pattern. Despite higher math scores and only a 0.154σ difference in the socioeconomic index, there is a 1.67 to 1.53σ difference in SVA on extraordinary admissions for all and top-10 private universities. The lack of difference in SVA on enrollment is explained by these comparable schools having a higher SVA on exam admissions at private universities. By contrast, COAR schools (column 4) have, on average, graduates with higher math scores and a non-statistically significant difference from IB schools in SVA on top-10 extraordinary admissions.

The conclusions for schools on the preferred schools list for top-10 universities are similar. Comparable schools in SVA and average scores have lower SVA on enrollment at all and top-10 private universities, with larger differences in extraordinary admissions. In contrast, COAR schools, despite having a lower average socioeconomic index, show similar SVA on enrollment at top-10 private universities and even a higher SVA of 1.84σ on extraordinary admissions. Appendix Table A.11 shows similar findings for schools on the top-5 and top-20 lists.

6 Conclusion

This paper explores the relationship between school reputation and effectiveness in learning with school effects on college outcomes in Peru, a country without a high school exit standardized test. We first estimate the impact of the COAR Network, a set of selective public schools, on college outcomes. Our estimates show positive impacts on enrollment, especially at top private institutions, with extraordinary admissions explaining between 40% to 60% of the total enrollment effects. We argue and provide further evidence that while human capital differences are unlikely to explain these effects, the results are consistent with COAR graduation signaling applicants' ability.

We complement this analysis by estimating SVA models on test scores and college outcomes for other secondary schools in Peru. We first validate these SVA estimates through two tests. First, we use the COAR assignment and find consistent effects between this quasi-experimental variation and the observational SVA estimates. Second, we demonstrate that the relationship between SVA estimates and student outcomes remains similar even after controlling for unobservable factors.

We estimate the relationship between SVA on college outcomes, SVA on learning, and average graduates' characteristics. After accounting for average scores and socioeconomic background, our results indicate that SVA on learning has little predictive power for school effects on college outcomes. Instead, the average socioeconomic index of a school explains most of the variation, especially at private universities through extraordinary admissions. Despite not generating significant human capital gains, COAR schools have a similar or larger SVA on enrollment and extraordinary admissions to top private universities compared to other eligible schools. Thus, COAR schools offer talented low-income students a signal that helps reduce income gaps and segregation in college access.

Overall, the results indicate that in the absence of test scores, college admissions authorities place greater emphasis on alternative information sources, such as the reputation of the graduating school. This reputation is closely tied to a school's average socioeconomic background. These findings suggest that the debate on the distributional consequences of standardized tests in college admissions should consider the potential bias in test scores against the persistent gaps arising from unequal access to prestigious secondary schools.

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Table 1: College Admissions by Type of University and Admission Mode

Ranking	Private university			Public university		
	Exam	Extraordinary	Preparatory	Exam	Extraordinary	Preparatory
	(1)	(2)	(3)	(4)	(5)	(6)
Top 10	36.86	54.98	8.17	67.39	8.30	24.31
Top 20	38.97	54.53	6.50	76.95	9.15	13.89
Top 32	74.24	15.67	10.09	72.13	9.05	18.83
Unranked	63.91	31.59	4.50	65.45	11.37	23.18

Notes: This table reports the proportion of admitted applicants by each admission mode between 2017 and 2022. Columns 1 to 3 report admission rates of private universities, and columns 4 to 6 of public universities.

Table 2: First Stage and Average Graduates Characteristics

	COAR network			Average graduates characteristics		
	Offer	Enrollment	Graduation	Math scores	Reading scores	Socioeconomic index
	(1)	(2)	(3)	(4)	(5)	(6)
Clears qualifying cutoff	1.000***	0.522***	0.469***			
	(0.000)	(0.020)	(0.021)			
COAR Graduate				1.651***	1.370***	0.242***
				(0.057)	(0.051)	(0.064)
Control mean	0.000	0.061	0.055	0.185	0.151	-0.070
Bandwidth	1.772	1.772	1.772	1.772	1.772	1.772
F-Statistic				373.727	373.727	373.727
Observations	9,159	9,159	9,159	6,943	6,943	6,943

Notes: This table reports COAR effects on first-stage-related outcomes. Columns 1 to 3 report reduced-form estimates of clearing the qualifying cutoff on the likelihood of an offer, enrollment, and graduation from the COAR Network. Columns 4 to 6 report 2SLS estimates of COAR graduation on average high school graduates characteristics using the single-offer model. All estimates control for baseline math and reading scores. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 3: 2SLS Estimates of COAR Graduation on College Enrollment

	All universities (1)	Private university (2)	Public university (3)	Top-10 university (4)	Top-10 private university (5)	Top-10 public university (6)
A. Single-offer model						
COAR graduate	0.119**	0.196***	-0.046	0.154***	0.158***	0.001
	(0.054)	(0.061)	(0.059)	(0.047)	(0.038)	(0.033)
Control mean	0.715	0.355	0.388	0.145	0.062	0.083
Bandwidth	1.772	1.772	1.772	1.772	1.772	1.772
First-stage F-stat	478.557	478.557	478.557	478.557	478.557	478.557
Observations	9,159	9,159	9,159	9,159	9,159	9,159
B. Multiple-offers model						
COAR graduate	0.091***	0.174***	-0.079**	0.080***	0.094***	-0.017
	(0.030)	(0.035)	(0.035)	(0.027)	(0.022)	(0.019)
Control mean	0.699	0.347	0.378	0.137	0.055	0.083
First-stage F-stat	72.447	72.447	72.447	72.447	72.447	72.447
Overid p-value	0.567	0.523	0.203	0.054	0.102	0.039
Observations	13,113	13,113	13,113	13,113	13,113	13,113

Notes: This table reports 2SLS estimates of COAR graduation on college enrollment outcomes. Panels A and B report 2SLS estimates using the single- and multiple-offers models, respectively. All models control for baseline math and reading scores. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for the outcome of any college enrollment. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 4: 2SLS Estimates of COAR Graduation on Application, Admission, and Enrollment by Type of University

	Private university			Public university		
	Application	Admission	Enrollment	Application	Admission	Enrollment
	(1)	(2)	(3)	(4)	(5)	(6)
I. All universities						
A. Single-offer model						
COAR graduate	0.357***	0.224***	0.196***	-0.001	-0.057	-0.046
	(0.065)	(0.060)	(0.061)	(0.061)	(0.058)	(0.059)
Control mean	0.452	0.375	0.355	0.720	0.376	0.388
Bandwidth	1.474	1.799	1.772	1.474	1.799	1.772
First-stage F-stat	381.091	491.260	478.557	381.091	491.260	478.557
Observations	8,030	9,278	9,159	8,030	9,278	9,159
B. Multiple-offers model						
COAR graduate	0.277***	0.197***	0.174***	-0.020	-0.071**	-0.079**
	(0.036)	(0.034)	(0.035)	(0.033)	(0.033)	(0.035)
Control mean	0.441	0.362	0.347	0.718	0.368	0.378
First-stage F-stat	62.550	78.168	72.447	62.550	78.168	72.447
Overid p-value	0.000	0.096	0.523	0.033	0.109	0.203
Observations	12,805	13,469	13,113	12,805	13,469	13,113
II. Top-10 universities						
A. Single-offer model						
COAR graduate	0.395***	0.209***	0.158***	0.142**	-0.003	0.001
	(0.054)	(0.039)	(0.038)	(0.056)	(0.033)	(0.033)
Control mean	0.128	0.066	0.062	0.235	0.087	0.083
Bandwidth	1.474	1.799	1.772	1.474	1.799	1.772
First-stage F-stat	381.091	491.260	478.557	381.091	491.260	478.557
Observations	8,030	9,278	9,159	8,030	9,278	9,159
B. Multiple-offers model						
COAR graduate	0.297***	0.146***	0.094***	0.106***	-0.020	-0.017
	(0.030)	(0.023)	(0.022)	(0.030)	(0.018)	(0.019)
Control mean	0.122	0.060	0.055	0.229	0.085	0.083
First-stage F-stat	62.550	78.168	72.447	62.550	78.168	72.447
Overid p-value	0.000	0.003	0.102	0.010	0.012	0.039
Observations	12,805	13,469	13,113	12,805	13,469	13,113

Notes: This table reports 2SLS estimates of COAR graduation on college application, admission, and enrollment by type of university. Section I reports estimates on application, admission, and enrollment at any university, while section II reports the same estimates for top-10 universities. Panels A and B report 2SLS estimates using the single- and multiple-offers models, respectively. All models control for baseline math and reading scores. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for a general application, admission, and enrollment outcomes. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 5: 2SLS Estimates of COAR Graduation by Type of Admission for Private Universities

	Exam		Extraordinary		Academy	
	Application	Admission	Application	Admission	Application	Admission
	(1)	(2)	(3)	(4)	(5)	(6)
I. All private universities						
A. Single-offer model						
COAR graduate	0.227***	0.117**	0.303***	0.165***	-0.021	-0.012
	(0.064)	(0.053)	(0.064)	(0.052)	(0.024)	(0.015)
Control mean	0.277	0.219	0.270	0.184	0.028	0.015
Bandwidth	1.474	1.799	1.474	1.799	1.474	1.799
First-stage F-stat	381.091	491.260	381.091	491.260	381.091	491.260
Observations	8,030	9,278	8,030	9,278	8,030	9,278
B. Multiple-offers model						
COAR graduate	0.167***	0.086***	0.246***	0.150***	-0.006	0.003
	(0.036)	(0.030)	(0.035)	(0.030)	(0.014)	(0.009)
Control mean	0.267	0.210	0.263	0.178	0.028	0.015
First-stage F-stat	62.550	78.168	62.550	78.168	62.550	78.168
Overid p-value	0.277	0.011	0.000	0.000	0.721	0.430
Observations	12,805	13,469	12,805	13,469	12,805	13,469
II. Top-10 private Universities						
A. Single-offer model						
COAR graduate	0.214***	0.113***	0.274***	0.102***	-0.007	-0.012
	(0.045)	(0.028)	(0.048)	(0.032)	(0.011)	(0.008)
Control mean	0.067	0.027	0.083	0.041	0.005	0.003
Bandwidth	1.474	1.799	1.474	1.799	1.474	1.799
First-stage F-stat	381.091	491.260	381.091	491.260	381.091	491.260
Observations	8,030	9,278	8,030	9,278	8,030	9,278
B. Multiple-offers model						
COAR graduate	0.189***	0.096***	0.180***	0.069***	-0.008	-0.008**
	(0.025)	(0.016)	(0.027)	(0.019)	(0.006)	(0.004)
Control mean	0.067	0.025	0.078	0.036	0.004	0.002
First-stage F-stat	62.550	78.168	62.550	78.168	62.550	78.168
Overid p-value	0.000	0.007	0.000	0.014	0.617	0.864
Observations	12,805	13,469	12,805	13,469	12,805	13,469

Notes: This table reports 2SLS estimates of COAR graduation on applications and admissions at private universities by type of admission. Sections I and II report results for all and top-10 private universities, respectively. Panels A and B report 2SLS estimates using the single- and multiple-offers models, respectively. All models control for baseline math and reading scores. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for a general application and admission outcomes. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 6: Reduced-Form and 2SLS Estimates of COAR Graduation on Admission Exams Performance

	p-value >= 0.05			p-value >= 0.1		
Dependent variable:	Has exam score	Exam score		Has exam score	Exam score	
		Reduced-Form	2SLS		Reduced-Form	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
A. Balanced attrition for single-offer model						
Clears qualifying cutoff	-0.005	0.011		0.012	-0.003	
	(0.026)	(0.048)		(0.026)	(0.049)	
COAR graduate			0.023			-0.006
			(0.113)			(0.118)
Control mean	0.673	0.299	0.299	0.648	0.297	0.297
Bandwidth	1.881	1.881	1.881	1.881	1.881	1.881
First-stage F-stat			286.88			258.08
Observations	9,517	13,089	13,089	9,517	12,582	12,582
B. Balanced attrition for multiple-offers model						
COAR graduate			0.015			0.006
			(0.083)			(0.083)
Control mean			0.310			0.313
First-stage F-stat			30.207			29.497
Overid p-value			0.268			0.255
Observations			13,709			13,523

Notes: This table reports reduced-form and 2SLS estimates of COAR graduation on the likelihood of reporting a university admission exam and the exam performance under two balanced attrition samples. Columns 1-3 and columns 4-6 exclude universities where the p-value of the tests that the estimates of clearing the admission cutoff and the estimates of all offers on observing an exam score are less than 0.05 and 0.1, respectively. Panels A and B report estimates using the single- and multiple-offers models, respectively. All models control for baseline math and reading scores. Estimates on exam performance (columns 2-3 and columns 5-6) also control for university-admission period fixed effects. Exam scores are standardized at the university, major, and admission period level. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for the outcome of the exam score. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 7: 2SLS Estimates of COAR Graduation on Eligibility for Extraordinary Admissions

	All universities			Private universities			Public universities		
	Preferred	IB diploma		Preferred	IB diploma		Preferred	IB diploma	
	school	Eligible	Received	school	Eligible	Received	school	Eligible	Received
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I. All universities									
A. Single-offer model									
COAR graduate	28.184***	21.351***	6.374***	9.456***	17.351***	5.240***	18.727***	4.000***	1.134***
	(0.106)	(0.109)	(0.958)	(0.117)	(0.109)	(0.788)	(0.050)	(0.000)	(0.170)
Control mean	3.816	2.415	0.193	1.378	1.972	0.159	2.438	0.443	0.034
Bandwidth	0.493	0.663	2.494	0.493	0.663	2.494	0.493	0.663	2.494
First-stage F-stat	122.168	168.177	358.364	122.168	168.177	358.364	122.168	168.177	358.364
Observations	2,855	3,838	6,710	2,855	3,838	6,710	2,855	3,838	6,710
B. Multiple-offers model									
COAR graduate	28.235***	21.343***	7.990***	9.496***	17.341***	6.560***	18.739***	4.002***	1.430***
	(0.046)	(0.057)	(0.787)	(0.051)	(0.056)	(0.647)	(0.022)	(0.003)	(0.140)
Control mean	1.711	1.194	0.195	0.655	0.975	0.161	1.056	0.220	0.035
First-stage F-stat	32.348	33.507	29.513	32.348	33.507	29.513	32.348	33.507	29.513
Overid p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
Observations	9,657	9,839	7,006	9,657	9,839	7,006	9,657	9,839	7,006
II. Top-10 universities									
A. Single-offer model									
COAR graduate	4.159***	7.000***	1.985***	2.159***	5.000***	1.418***	2.000***	2.000***	0.567***
	(0.062)	(0.000)	(0.298)	(0.062)	(0.000)	(0.213)	(0.000)	(0.000)	(0.085)
Control mean	0.580	0.776	0.060	0.320	0.554	0.043	0.260	0.222	0.017
Bandwidth	0.493	0.663	2.494	0.493	0.663	2.494	0.493	0.663	2.494
First-stage F-stat	122.168	168.177	358.364	122.168	168.177	358.364	122.168	168.177	358.364
Observations	2,855	3,838	6,710	2,855	3,838	6,710	2,855	3,838	6,710
B. Multiple-offers model									
COAR graduate	4.223***	7.003***	2.502***	2.223***	5.002***	1.787***	2.000***	2.001***	0.715***
	(0.027)	(0.006)	(0.245)	(0.027)	(0.004)	(0.175)	(0.000)	(0.002)	(0.070)
Control mean	0.263	0.385	0.061	0.151	0.275	0.043	0.112	0.110	0.017
First-stage F-stat	32.348	33.507	29.513	32.348	33.507	29.513	32.348	33.507	29.513
Overid p-value	0.000	1.000	0.000	0.000	1.000	0.000	.	1.000	0.000
Observations	9,657	9,839	7,006	9,657	9,839	7,006	9,657	9,839	7,006

Notes: This table reports 2SLS estimates of COAR graduation on eligibility for extraordinary admissions. Sections I and II report eligibility outcomes for all and top-10 universities, respectively. Panels A and B report estimates using the single- and multiple-offers models, respectively. Both models control for baseline math and reading scores. Results for the IB diploma consider whether the university considers IB admissions (eligible) and whether, in addition to being eligible, the applicant has earned the diploma (received). The latter information is not available for the 2017 COAR cohort. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for eligibility through the preferred school, the IB diploma, and the IB diploma adjusted by earning it outcomes. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 8: Reduced Form and 2SLS Estimates of the IB Diploma on College Outcomes for Top-10 Universities

	Exam		Extraordinary		Preparatory		Enrollment
	Application	Admission	Application	Admission	Application	Admission	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I. Private university							
A. Reduced form							
IB score = 24	-0.012	-0.000	0.054	0.079***	0.001	-0.006	0.128***
	(0.036)	(0.025)	(0.040)	(0.028)	(0.010)	(0.006)	(0.034)
Control mean	0.191	0.062	0.200	0.053	0.009	0.004	0.093
Observations	478	478	478	478	478	478	478
RI: p-value	0.773	1.000	0.186	0.007	1.000	0.333	0.000
B. Two-stage least squares							
IB diploma	-0.016	-0.000	0.073	0.107***	0.002	-0.008	0.173***
	(0.049)	(0.033)	(0.053)	(0.038)	(0.014)	(0.009)	(0.047)
Control mean	0.191	0.062	0.200	0.053	0.009	0.004	0.093
Observations	478	478	478	478	478	478	478
II. Public university							
A. Reduced form							
IB score = 24	0.006	0.000	0.003	0.002	-0.007	0.005	-0.003
	(0.039)	(0.018)	(0.026)	(0.014)	(0.015)	(0.010)	(0.022)
Control mean	0.267	0.036	0.084	0.018	0.036	0.013	0.058
Observations	478	478	478	478	478	478	478
RI: p-value	0.895	1.000	1.000	1.000	0.772	1.000	1.000
B. Two-stage least squares							
IB diploma	0.009	0.000	0.004	0.002	-0.010	0.006	-0.004
	(0.053)	(0.025)	(0.035)	(0.019)	(0.020)	(0.013)	(0.029)
Control mean	0.267	0.036	0.084	0.018	0.036	0.013	0.058
Observations	478	478	478	478	478	478	478

Notes: This table reports reduced form and 2SLS estimates of the IB diploma on college outcomes for top-10 universities. The models use whether the student scored 24 vs. 23 points as an instrument for receiving the diploma. Sections I and II report the estimates for private and public universities, and panels A and B report reduced form and 2SLS estimates, respectively. The table also reports randomization inference p-values for the reduced form estimates. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table 9: Test for Bias in SVA Models on College Outcomes

Outcome variable:	Forecast coefficient			Overid test		First-stage
	$\hat{\phi}$	s.e.	$\phi = 1$ p-value	$\chi^2(22)$	p-value	F-stat
	(1)	(2)	(3)	(4)	(5)	(6)
A. Enrollment outcomes						
Any enrollment	1.085	0.340	0.803	22.342	0.440	17.065
Private enrollment	1.022	0.274	0.936	16.571	0.787	30.770
Public enrollment	1.094	0.338	0.781	19.213	0.632	29.368
Top-10 enrollment	0.771	0.277	0.408	21.722	0.477	34.527
Top-10 private enrollment	0.751	0.226	0.270	21.011	0.520	40.475
Top-10 public enrollment	1.685	0.643	0.286	18.539	0.674	16.757
B. Admission outcomes						
Private admission	0.871	0.205	0.529	19.062	0.642	40.782
Public admission	1.266	0.371	0.474	16.672	0.781	29.859
Top-10 private admission	1.069	0.211	0.745	24.378	0.328	51.046
Top-10 public admission	1.574	0.708	0.417	19.282	0.628	12.134
C. Admission modes for private universities						
Exam admission	1.015	0.256	0.952	19.000	0.645	26.545
Extraordinary admission	1.115	0.195	0.556	17.795	0.718	46.786
Exam top-10 admission	1.584	0.345	0.090	35.097	0.038	23.708
Extraordinary top-10 admission	0.927	0.288	0.801	22.046	0.457	48.960
D. Admission modes for public universities						
Exam admission	1.614	0.421	0.145	24.112	0.341	18.156
Extraordinary admission	0.804	0.471	0.678	34.665	0.042	47.048
Exam top-10 admission	1.749	0.682	0.273	33.774	0.052	26.708
Extraordinary top-10 admission	2.822	0.663	0.006	43.580	0.004	46.805

Notes: This table reports the results of tests for bias in school value-added models on college outcomes using the variation from the COAR mechanism in 1st-round COAR school offers. The sample corresponds to students taking the secondary school standardized test in 2015-16, which overlaps with COAR applicants in the 2016-17 application cycles. Column 1 reports the forecast coefficient estimate $\hat{\phi}$ from the 2SLS model in equation 11a, with column 2 reporting the associated robust standard error. Column 3 reports the p-value of the test of the forecast coefficient, ϕ, being equal to 1. Columns 4 and 5 report the over-identification test and the p-value, and column 6 reports the associated first-stage F-statistic of the model in equation 11b. The number of observations for enrollment outcomes in Panel A is 9,400 and for admission outcomes in Panels B, C, and is 9,141.

Table 10: Tests for Bias in SVA on College Outcomes and Learning due to Unobservables

Outcome:	All sample	Sample with household address in 2017 Census		Households with students in multiple schools	
	OLS	OLS	2SLS	OLS	Household FE
	(1)	(2)	(3)	(4)	(5)
A. Learning outcomes					
Math	0.271***	0.271***	0.281***	0.276***	0.269***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.009)
Reading	0.277***	0.277***	0.322***	0.291***	0.261***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.009)
Total score	0.314***	0.313***	0.341***	0.324***	0.305***
	(0.002)	(0.003)	(0.005)	(0.005)	(0.009)
Observations	825,113	506,643	506,643	68,051	68,051
B. Enrollment outcomes					
Any enrollment	0.124***	0.122***	0.117***	0.123***	0.126***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Private enrollment	0.134***	0.133***	0.143***	0.135***	0.127***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Public enrollment	0.068***	0.070***	0.074***	0.061***	0.062***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Top-10 private enrollment	0.042***	0.042***	0.044***	0.044***	0.040***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.003)
Top-10 public enrollment	0.031***	0.032***	0.031***	0.031***	0.033***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Observations	827,701	512,425	512,425	68,347	68,347
C. Admission outcomes					
Private admission	0.132***	0.131***	0.142***	0.134***	0.123***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Public admission	0.068***	0.070***	0.074***	0.060***	0.060***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Top-10 private admission	0.046***	0.047***	0.049***	0.048***	0.046***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Top-10 public admission	0.033***	0.034***	0.033***	0.033***	0.034***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Observations	827,701	512,425	512,425	68,347	68,347

Notes: This table reports tests for bias in SVA on college outcomes and learning due to unobservables. Column 1 reports the OLS estimate of a one-standard-deviation increase in SVA on students' individual outcomes. Columns 2 and 4 report this same estimate for students with the household address in the 2017 Census and for students in households where children attend multiple secondary schools, respectively. Column 3 reports the 2SLS estimate using the SVA of the closest school as an instrument for the SVA of the attended school, and column 5 includes a household fixed effects. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

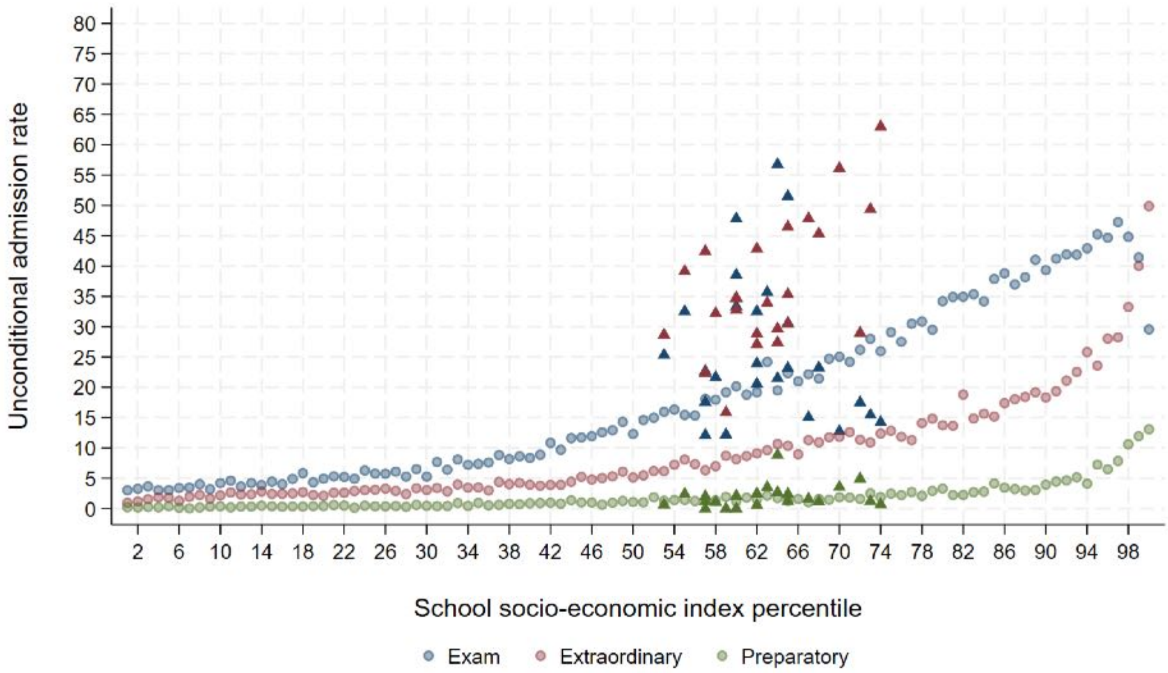
Table 11: Eligible Schools for Extraordinary Admissions vs. Comparable Schools in SVA on Learning, Average Scores, and COAR Schools

Variable:	IB Schools				Top-10 List			
	Mean	Comp. SVA learning	Comp. av. scores	COAR schools	Mean	Comp. SVA learning	Comp. av. scores	COAR schools
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Value-added to learning								
SVA math	2.307	0.112	0.213		1.500	0.026	0.151	
	[0.873]	(0.071)	(0.192)		[0.860]	(0.021)	(0.124)	
SVA reading	2.484	-0.025	-0.051		1.633	-0.008	-0.008	
	[0.537]	(0.033)	(0.112)		[0.764]	(0.008)	(0.094)	
SVA total	2.488	0.050	0.087		1.626	0.013	0.077	
	[0.700]	(0.045)	(0.148)		[0.800]	(0.013)	(0.104)	
B. Average scores								
Av. math score secon. school	2.394	-0.283***	0.258*	0.945***	1.829	-0.487***	-0.047	1.510***
	[0.658]	(0.097)	(0.138)	(0.197)	[0.606]	(0.046)	(0.090)	(0.152)
Av. reading score secon. school	2.396	-0.346***	0.108	0.102	1.825	-0.467***	-0.116	0.673***
	[0.418]	(0.072)	(0.086)	(0.126)	[0.496]	(0.037)	(0.079)	(0.099)
Av. socioeconomic index	1.759	-0.385***	-0.154***	-1.329***	1.488	-0.504***	-0.212***	-1.058***
	[0.080]	(0.082)	(0.058)	(0.069)	[0.246]	(0.045)	(0.050)	(0.068)
C. SVA on college enrollment								
Private enrollment	1.960	0.077	0.314	-1.136***	1.886	-1.024***	-0.510***	-1.062***
	[1.109]	(0.228)	(0.217)	(0.235)	[0.872]	(0.099)	(0.147)	(0.168)
Public enrollment	-2.001	1.327***	0.711***	1.394***	-0.867	0.927***	1.011***	0.261
	[0.469]	(0.207)	(0.261)	(0.271)	[1.176]	(0.146)	(0.278)	(0.267)
Top-10 private enrollment	3.150	-0.847	0.271	-0.256	2.527	-2.662***	-2.459***	0.366
	[2.004]	(0.538)	(0.811)	(0.422)	[2.501]	(0.206)	(0.229)	(0.320)
Top-10 public enrollment	-1.474	0.992***	0.275*	0.864***	-0.068	0.138	-0.281	-0.542**
	[0.536]	(0.183)	(0.161)	(0.248)	[1.424]	(0.154)	(0.193)	(0.251)
D. SVA on college admissions								
Private admission	1.890	0.094	0.359*	-0.925***	1.827	-0.977***	-0.457***	-0.862***
	[1.037]	(0.210)	(0.190)	(0.244)	[0.827]	(0.098)	(0.141)	(0.192)
Public admission	-2.046	1.305***	0.624**	1.587***	-0.833	0.874***	0.795***	0.374
	[0.469]	(0.206)	(0.248)	(0.268)	[1.250]	(0.146)	(0.204)	(0.266)
Top-10 private admission	3.077	-0.524	0.559	-0.074	2.654	-2.827***	-2.602***	0.349
	[1.718]	(0.503)	(0.811)	(0.442)	[2.323]	(0.217)	(0.218)	(0.381)
Top-10 public admission	-1.434	0.908***	0.210	1.070***	-0.110	0.166	-0.258	-0.254
	[0.489]	(0.165)	(0.142)	(0.242)	[1.344]	(0.148)	(0.185)	(0.246)
E. SVA on admission modes for private universities								
Exam admission	-0.507	1.568***	1.624***	0.498*	0.927	-0.190	0.288*	-0.937***
	[1.299]	(0.287)	(0.335)	(0.292)	[1.319]	(0.129)	(0.148)	(0.239)
Extra. admission	3.558	-1.900***	-1.673***	-1.663***	1.765	-1.538***	-1.345***	0.130
	[1.636]	(0.377)	(0.417)	(0.488)	[1.689]	(0.156)	(0.203)	(0.435)
Top-10 exam admission	0.631	1.356***	2.222**	0.815	1.819	-2.046***	-1.582***	-0.373
	[1.515]	(0.510)	(1.117)	(0.601)	[2.983]	(0.290)	(0.275)	(0.576)
Top-10 extra. admission	4.572	-2.469***	-1.534**	-0.420	2.315	-2.479***	-2.573***	1.837***
	[2.440]	(0.621)	(0.723)	(0.603)	[2.493]	(0.191)	(0.172)	(0.498)
F. SVA on admission modes for public universities								
Exam admission	-1.886	1.385***	0.758**	1.101***	-0.653	0.846***	0.773***	-0.132
	[0.443]	(0.254)	(0.312)	(0.329)	[1.289]	(0.156)	(0.210)	(0.327)
Extra. admission	-0.962	0.341***	0.072	1.943***	-0.650	0.331***	0.246***	1.630***
	[0.332]	(0.075)	(0.082)	(0.507)	[0.607]	(0.082)	(0.091)	(0.500)
Top-10 exam admission	-1.454	0.990***	0.295*	0.790***	0.046	0.104	-0.299	-0.711**
	[0.511]	(0.176)	(0.165)	(0.276)	[1.553]	(0.153)	(0.206)	(0.284)
Top-10 extra. admission	-0.600	0.175**	0.000	0.803	-0.387	0.127**	0.059	0.591
	[0.529]	(0.085)	(0.086)	(0.690)	[0.518]	(0.059)	(0.075)	(0.680)
Observations	48	152	85	70	384	536	462	406

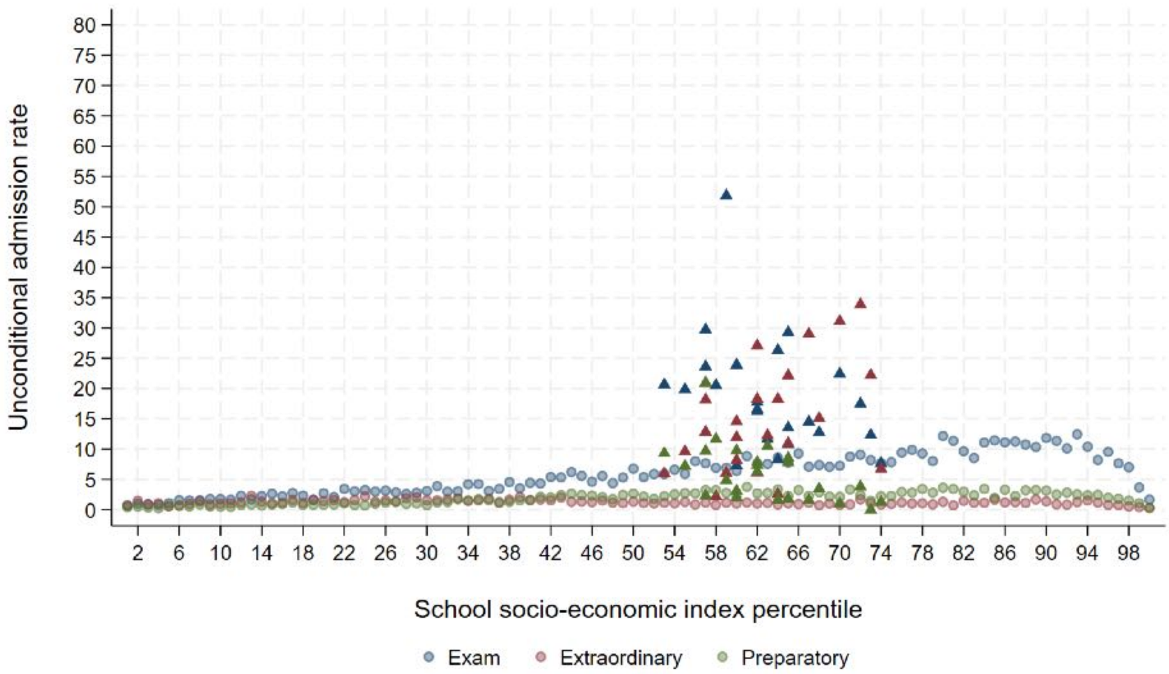
Notes: This table reports differences between schools eligible for extraordinary admissions and comparable schools in SVA on learning, average graduates' scores, and COAR schools. Columns 1 to 4 report differences for schools offering the IB program and columns 5 to 8 for schools on the list of preferred schools for top-10 private universities. Columns 1 and 5 report the mean for each group, columns 2 and 6 differences with comparable schools in SVA on learning, columns 3 and 7 differences with comparable schools in average scores, and columns 4 and 8 differences with COAR schools. Standard deviations are reported in squared brackets, and robust standard errors in parentheses; *significant at 10%, **significant at 5%, ***significant at 1%.

Figure 1: College Admissions by Secondary School Characteristics

(A) Private universities

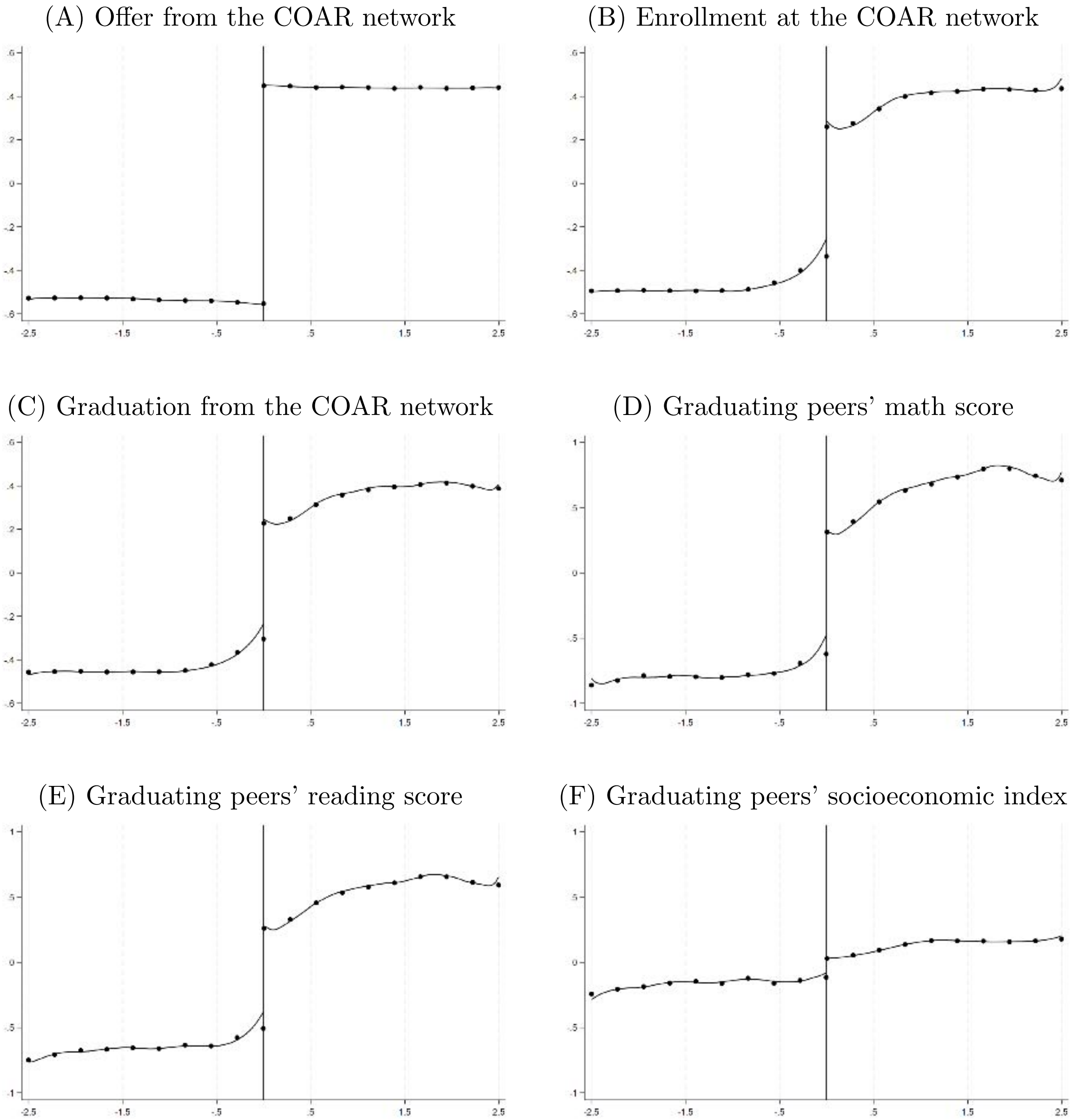


(B) Public universities



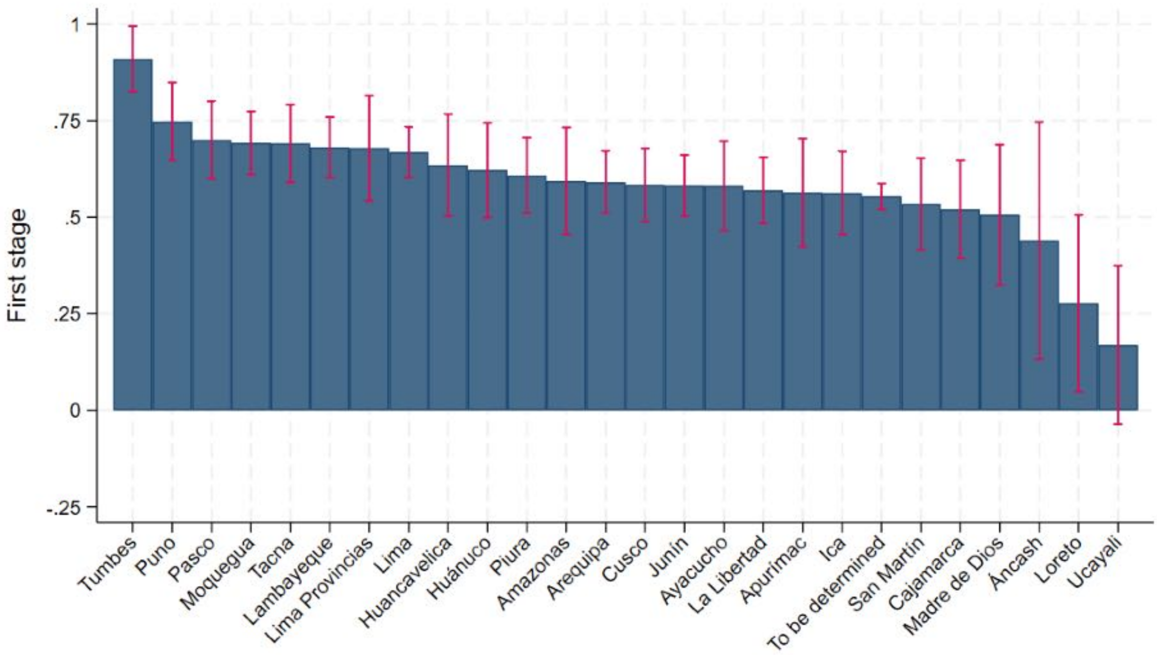
Notes: This figure shows the unconditional admission rate for three different admission modes over the percentiles of the average school socioeconomic index. Panel A plots these rates for private universities, and panel B for public universities. Triangle markers represent COAR schools, while circle markers denote all other schools.

Figure 2: COAR Network First Stage



Notes: This figure plots six first-stage outcomes near the region-specific qualifying cutoffs against the COAR Network school running variable. All outcomes are plotted after partialing out risk sets. The black dots represent the bins of the outcomes in different values of the running variable; lines in the plots are estimated conditional mean functions smoothed using local polynomial regression with a square polynomial.

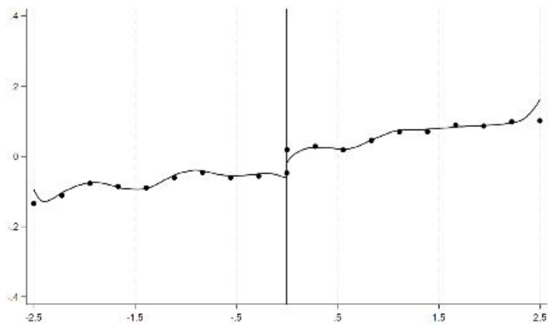
Figure 3: Effects of School-Specific Offers on COAR Graduation



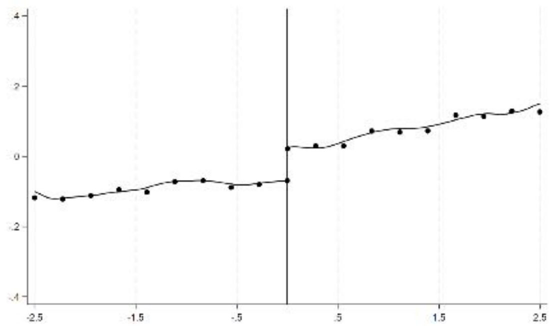
Notes: This figure reports estimates of the first-stage effects of individual COAR school offers on COAR graduation using the multiple-offers model. Whiskers mark 95% confidence intervals.

Figure 4: COAR Network Reduced-Form Effects

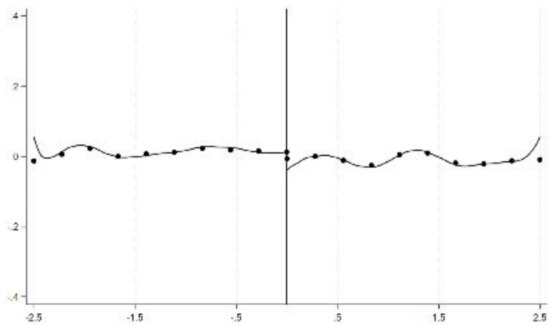
(A) Enrollment at any university



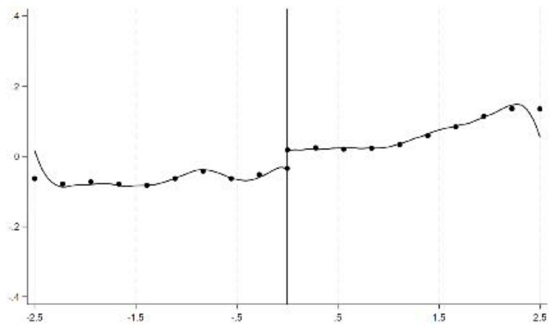
(B) Enrollment private universities



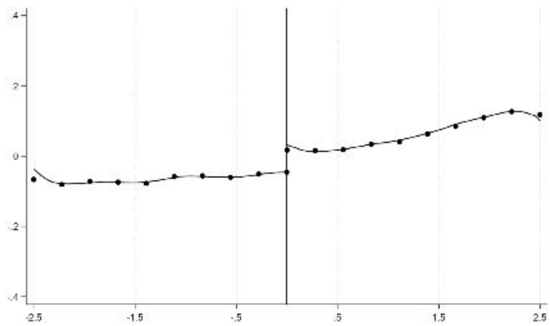
(C) Enrollment at public universities



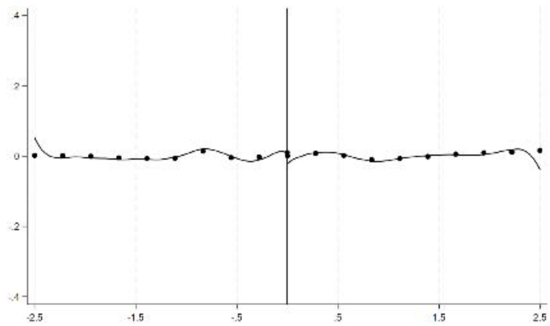
(D) Enrollment at top-10 universities



(E) Enrollment at top-10 private universities

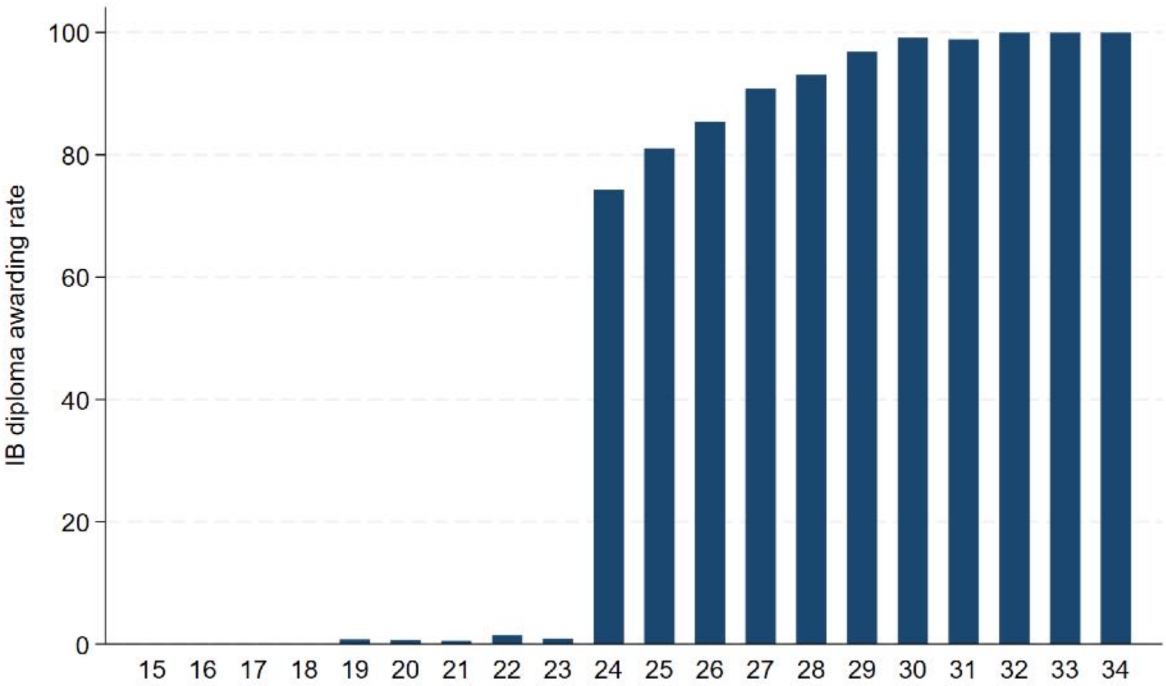


(F) Enrollment at top-10 public universities



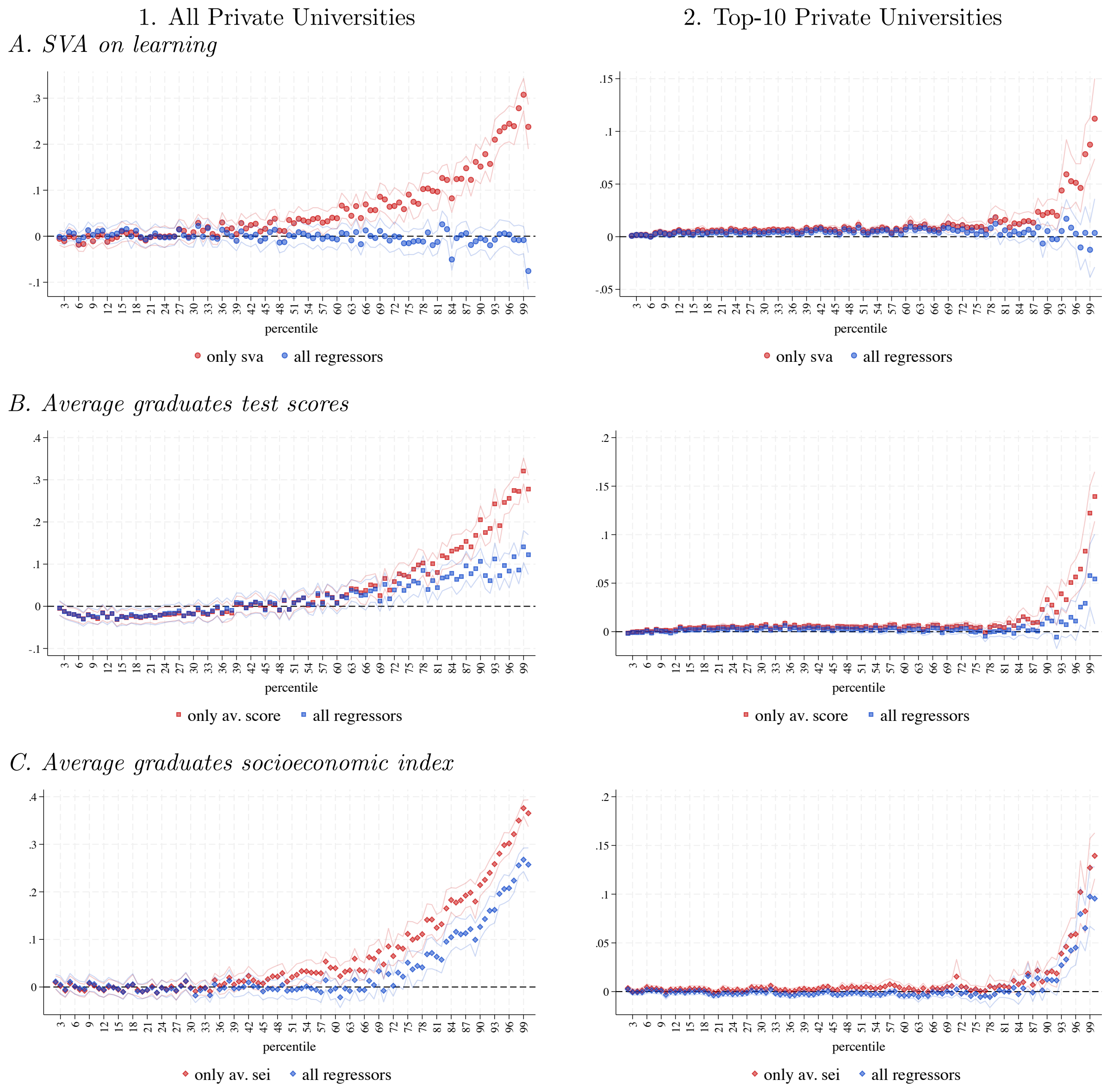
Notes: This figure plots six university enrollment outcomes near the region-specific qualifying cutoffs against the COAR Network school running variable. All outcomes are plotted after partialing out risk sets. The black dots represent the bins of the outcomes in different values of the running variable; lines in the plots are estimated conditional mean functions smoothed using local polynomial regression with a square polynomial.

Figure 5: International Baccalaureate First Stage



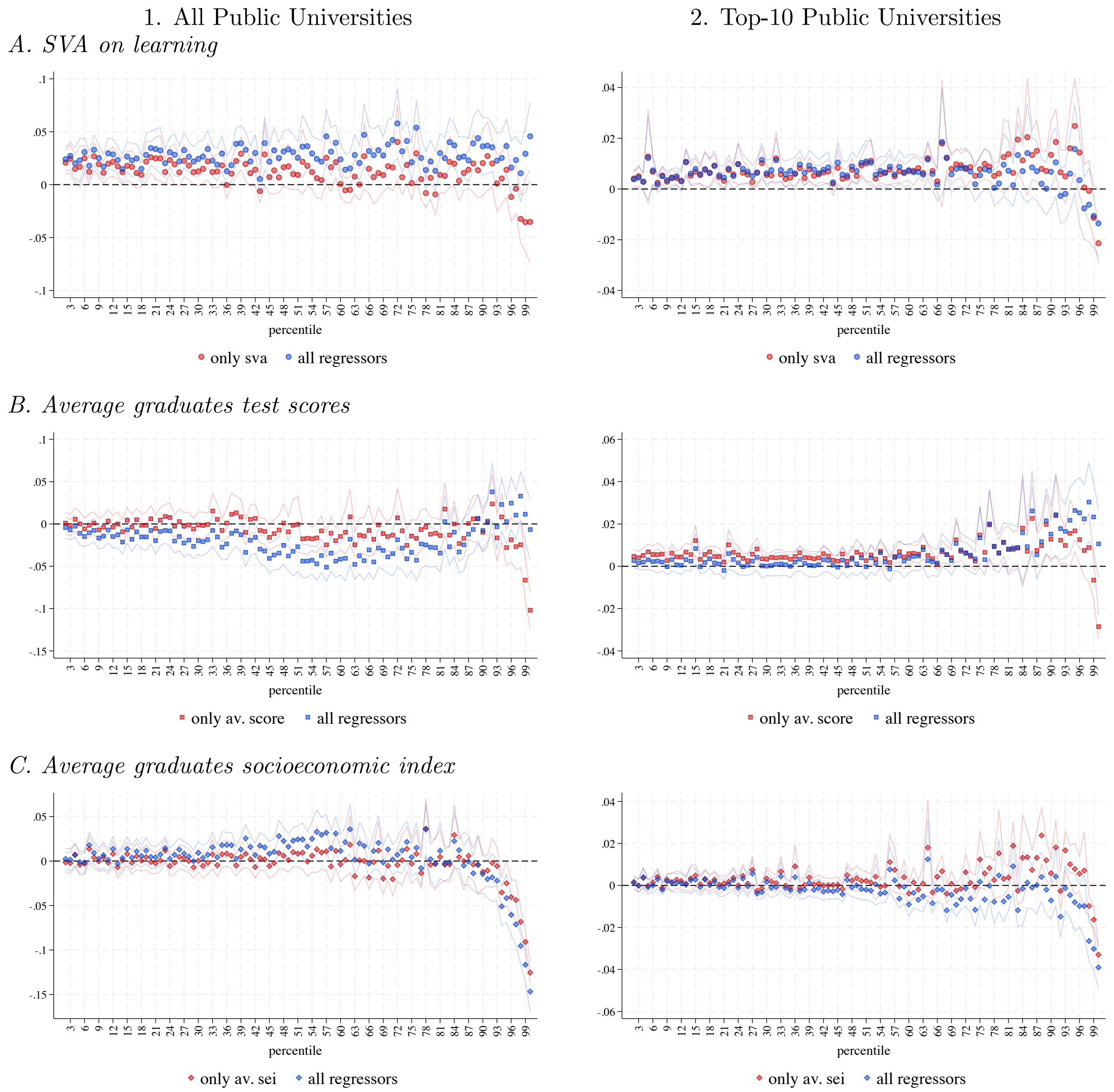
Notes: This figure shows the likelihood of receiving the IB Diploma at different values of the final score in the IB Program. Our estimates in Table 8 compares students who scored 23 vs. those who scored 24 points.

Figure 6: SVA on College Enrollment at Private Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics



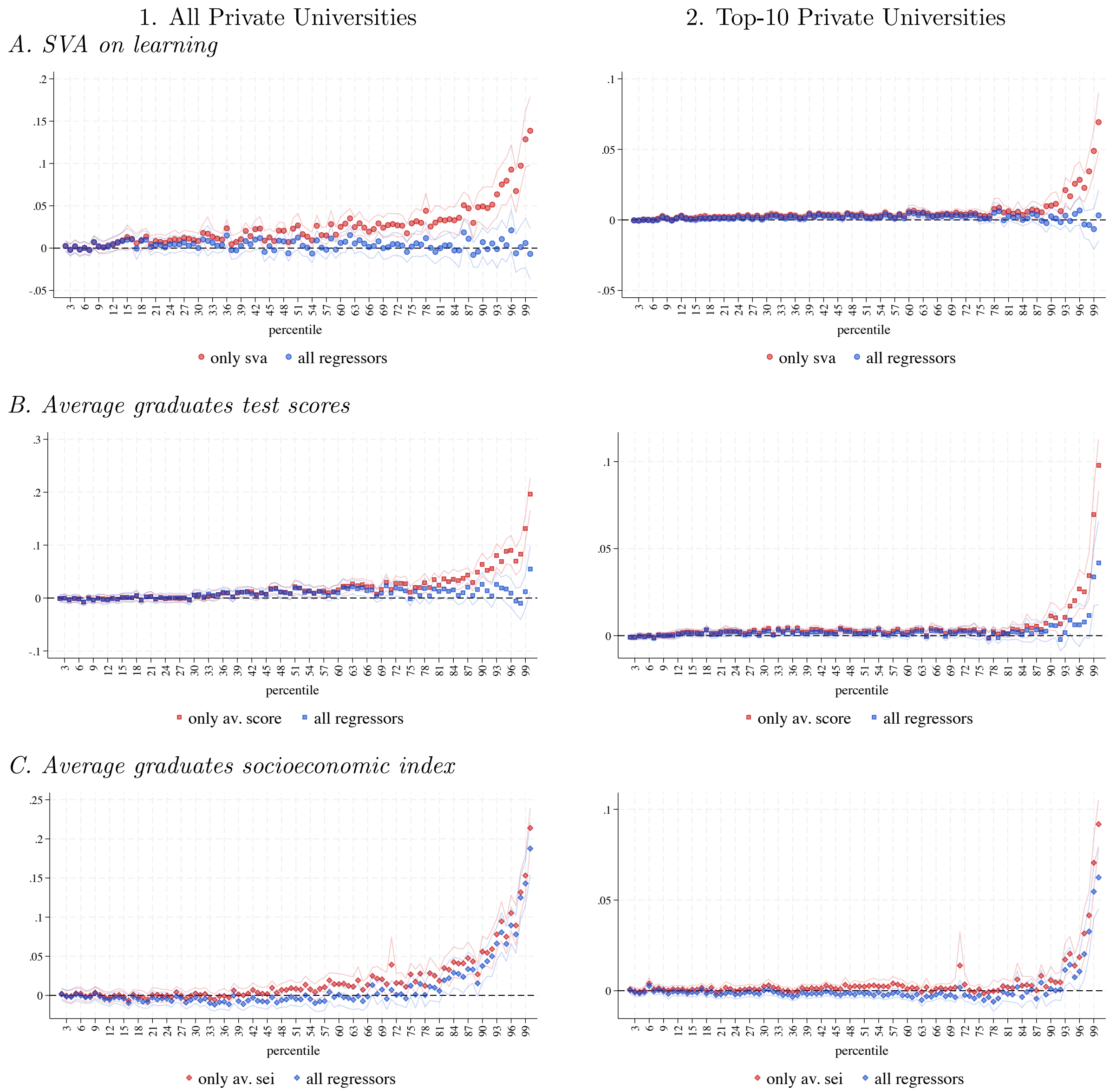
Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college enrollment at private universities. Column 1 reports the effects for all private universities, and column 2 for top-10 private universities. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

Figure 7: SVA on College Enrollment at Public Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics



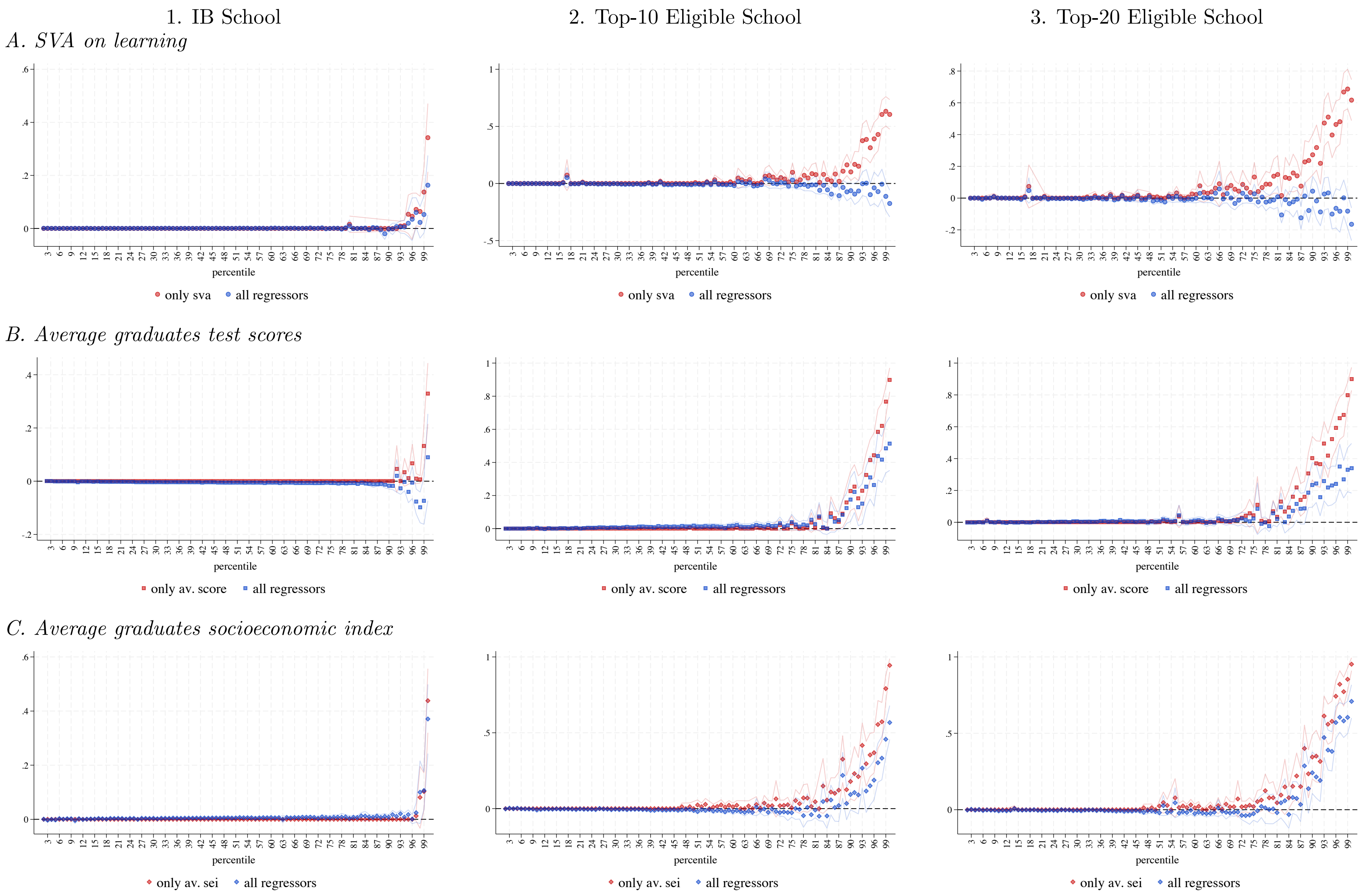
Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college enrollment at public universities. Column 1 reports the effects for all public universities, and column 2 for top-10 public universities. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

Figure 8: SVA on Extraordinary Admissions at Private Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics



Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on extraordinary admissions at private universities. Column 1 reports the effects for all private universities, and column 2 for top-10 private universities. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

Figure 9: Eligibility for Extraordinary Admissions vs. SVA on Learning and Graduates' Average Characteristics



Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on eligibility for extraordinary admissions at private universities. Column 1 reports the effects for IB school, and columns 2 and 3 for eligibility on extraordinary admissions top-10 and top-20 private universities, respectively. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

Appendix

A Additional Tables and Figures

Table A.1: Balance COAR RD

	Single-offer model					Multiple-offers model
	Observations	Control mean	Coefficient	S.E.	p-value	Offers = 0 (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)
I. COAR admission process						
Academic score	9,159	-0.229	0.008	0.043	0.853	0.184
Social score	9,159	-0.045	-0.034	0.030	0.269	0.679
Interview score	9,159	-0.022	0.008	0.025	0.760	0.368
II. Characteristics of the student and his/her school of origin						
Female	9,159	0.566	0.017	0.029	0.556	0.858
Spanish	9,159	0.917	-0.000	0.014	0.996	0.519
Urban school	9,158	0.906	0.005	0.016	0.731	0.456
Student-teacher ratio	9,158	14.838	0.230	0.314	0.464	0.229
III. 2nd-grade of secondary school standardized national tests						
Math	6,971	1.457	-0.053	0.067	0.428	0.210
Reading	6,971	1.222	-0.018	0.055	0.741	0.257
Socioeconomic index	6,947	0.082	-0.007	0.051	0.895	0.051
IV. Transcripts (2nd-grade of secondary school)						
Math	9,158	16.982	-0.122	0.093	0.189	0.474
Literature	9,158	16.668	-0.008	0.080	0.924	0.886
History and Geography	9,158	16.731	0.067	0.087	0.442	0.608
Science and Technology	9,158	16.710	0.037	0.086	0.670	0.376
English	9,158	16.695	0.042	0.089	0.639	0.583

Notes: This table reports balance tests for the COAR experiment around general and school-specific admissions cutoffs. Columns 1 to 5 report balance for the single-offer model, and column 6 for the multiple-offers model. Column 1 reports the number of observations, column 2 the control mean, column 3 the difference of clearing the general admission cutoff, column 4 the robust standard error of this difference, and column 5 the respective p-value of this difference being equal to zero. Column 6 reports the p-value of the joint significance test of the school-specific offers being equal to zero. Robust standard errors are shown in column (4): *significant at 10%, **significant at 5%, ***significant at 1%.

Table A.2: 2SLS Estimates of COAR Graduation by Type of Admission for Public Universities

	Exam		Extraordinary		Preparatory	
	Application	Admission	Application	Admission	Application	Admission
	(1)	(2)	(3)	(4)	(5)	(6)
I. All universities						
A. Single-offer model						
COAR graduate	0.058	0.018	0.050	-0.068*	0.008	0.006
	(0.067)	(0.048)	(0.060)	(0.041)	(0.052)	(0.031)
Control mean	0.611	0.213	0.245	0.112	0.191	0.063
Bandwidth	1.474	1.799	1.474	1.799	1.474	1.799
First-stage F-stat	381.091	491.260	381.091	491.260	381.091	491.260
Observations	8,030	9,278	8,030	9,278	8,030	9,278
B. Multiple-offers model						
COAR graduate	0.004	-0.027	0.008	-0.035	-0.012	-0.007
	(0.037)	(0.027)	(0.034)	(0.023)	(0.029)	(0.017)
Control mean	0.609	0.211	0.243	0.110	0.184	0.061
First-stage F-stat	62.550	78.168	62.550	78.168	62.550	78.168
Overid p-value	0.002	0.060	0.000	0.064	0.012	0.329
Observations	12,805	13,469	12,805	13,469	12,805	13,469
II. Top-10 universities						
A. Single-offer model						
COAR graduate	0.145***	0.017	0.025	-0.033	-0.004	0.021
	(0.055)	(0.026)	(0.037)	(0.021)	(0.027)	(0.016)
Control mean	0.204	0.048	0.074	0.030	0.039	0.012
Bandwidth	1.474	1.799	1.474	1.799	1.474	1.799
First-stage F-stat	381.091	491.260	381.091	491.260	381.091	491.260
Observations	8,030	9,278	8,030	9,278	8,030	9,278
B. Multiple-offers model						
COAR graduate	0.102***	0.004	-0.011	-0.026**	-0.009	0.005
	(0.030)	(0.014)	(0.020)	(0.011)	(0.015)	(0.009)
Control mean	0.201	0.047	0.071	0.029	0.036	0.013
First-stage F-stat	62.550	78.168	62.550	78.168	62.550	78.168
Overid p-value	0.038	0.015	0.039	0.000	0.397	0.019
Observations	12,805	13,469	12,805	13,469	12,805	13,469

Notes: This table reports 2SLS estimates of COAR graduation on applications and admissions at public universities by type of admission. Sections I and II report results for all and top-10 public universities, respectively. Panels A and B report 2SLS estimates using the single- and multiple-offers models, respectively. All models control for baseline math and reading scores. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for general application and admission outcomes. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table A.3: COAR: Hatrick & Paniagua (2020)'s Estimates

	Bandwidth	Observations	Control group mean	Estimates		
				Coefficient	p-value	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
A. Standardized tests						
Mathematics	0.42	862	-0.27	-0.03	0.68	0.073
Reading comprehension	0.46	916	-0.18	-0.02	0.74	0.060
B. Non-cognitive skills						
Leadership	0.45	898	-0.14	-0.07	0.50	0.104
School attitude	0.37	739	-0.05	-0.02	0.71	0.054
Grit	0.62	1198	-0.24	0.19	0.17	0.138
Stress	0.52	1032	-0.17	0.16	0.48	0.226
Self-sufficiency	0.53	1036	-0.28	0.14	0.33	0.144
Self-efficacy	0.63	1198	-0.19	0.08	0.74	0.241
Academic stress	0.55	1056	-0.01	0.03	0.95	0.478
C. Expectations						
Expectation of studying at university	0.43	887	0.63	0.135*	0.09	0.080

Notes: This table reports Hatrick & Paniagua (2020)'s estimates for the 2016 cohort on academic and social outcomes. Each outcome has been standardized and has their own Calonico, Cattaneo & Titiunik (2014) optimal bandwidth; ***significant at the 1 percent level, **significant at the 5 percent level, *significant at the 10 percent level.

Table A.4: Balance: IB Experiment

	Observations	Control mean	IB score = 24 points			
			Coefficient	S.E.	p-value	RI p-value
	(1)	(2)	(3)	(4)	(5)	(6)
A. Characteristics of the student						
Female	478	0.627	-0.033	0.046	0.474	0.497
Spanish	478	0.907	0.008	0.021	0.714	0.845
B. Social scores						
Centrality Social Network	477	0.387	0.023	0.019	0.231	0.248
Total Degree Social Network	477	13.045	0.407	0.513	0.428	0.439
Leadership: Peer perception	478	2.560	0.240	0.423	0.570	0.610
Leadership: Own perception	460	0.260	0.039	0.045	0.377	0.337
Grit	456	70.539	2.135	2.345	0.363	0.385
Empathy	444	33.100	0.496	0.532	0.352	0.353
Happiness	444	106.548	-0.122	1.389	0.930	0.942
Family Support	444	25.043	-0.383	0.405	0.345	0.357
Total Stress	444	52.014	-1.527	0.976	0.118	0.142
C. Academic scores						
Reading	478	0.008	0.031	0.058	0.590	0.616
Math	478	-0.124	0.060	0.067	0.368	0.394
Cognitive	478	0.026	-0.009	0.087	0.921	0.917

Notes: This table reports balance tests for the IB diploma experiment. The sample is restricted to COAR students who scored 24 and 23 points in the IB Diploma Program. The treatment variable is a dummy indicating whether the COAR student scored 24 points in the IB Diploma Program. Robust standard errors are shown in column (4): *significant at 10%, **significant at 5%, ***significant at 1%. Randomized-inference p-values are shown in column (5).

Table A.5: Reduced Form and 2SLS Estimates of COAR Graduation on Admission Exams Performance for All Universities

Dependent variable:	Exam application	Has exam score	Exam score	
			Reduced-form	2SLS
	(1)	(2)	(3)	(4)
A. Single-offer model				
Clears qualifying cutoff	0.036	0.029	0.028	
	(0.025)	(0.026)	(0.046)	
COAR graduate				0.059
				(0.110)
Control mean	0.721	0.681	0.300	0.300
Bandwidth	1.881	1.881	1.881	1.881
First-stage F-stat				300.52
Observations	9,517	9,517	13,939	13,939
B. Multiple-offers model				
COAR graduate				0.003
				(0.073)
Control mean				0.292
First-stage F-stat				33.866
Overid p-value				0.166
Observations				18,408

Notes: This table reports reduced-form and 2SLS estimates of COAR graduation on the likelihood of reporting a university admission exam and the exam performance. Panels A and B report estimates using the single- and multiple-offers models, respectively. All models control for baseline math and reading scores. Estimates on exam performance (columns 3-4) also control for university-admission period fixed effects. Exam scores are standardized at the university, major, and admission period level. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel for the outcome of the exam score. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table A.6: 2SLS Estimates of COAR Graduation on Eligibility for Extraordinary Admissions

	All universities			Private universities			Public universities		
	Preferred	IB diploma		Preferred	IB diploma		Preferred	IB diploma	
	school	Eligible	Received	school	Eligible	Received	school	Eligible	Received
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I. Eligibility from admission policies for top-10 universities									
A. Single-offer model									
COAR graduate	3.118***	7.000***	1.985***	1.118***	5.000***	1.418***	2.000***	2.000***	0.567***
	(0.077)	(0.000)	(0.298)	(0.077)	(0.000)	(0.213)	(0.000)	(0.000)	(0.085)
Control mean	0.426	0.776	0.060	0.166	0.554	0.043	0.260	0.222	0.017
Bandwidth	0.493	0.663	2.494	0.493	0.663	2.494	0.493	0.663	2.494
First-stage F-stat	122.168	168.177	358.364	122.168	168.177	358.364	122.168	168.177	358.364
Observations	2,855	3,838	6,710	2,855	3,838	6,710	2,855	3,838	6,710
B. Multiple-offers model									
COAR graduate	3.219***	7.003***	2.502***	1.219***	5.002***	1.787***	2.000***	2.001***	0.715***
	(0.039)	(0.006)	(0.245)	(0.039)	(0.004)	(0.175)	(0.000)	(0.002)	(0.070)
Control mean	0.201	0.385	0.061	0.089	0.275	0.043	0.112	0.110	0.017
First-stage F-stat	32.348	33.507	29.513	32.348	33.507	29.513	32.348	33.507	29.513
Overid p-value	0.000	1.000	0.000	0.000	1.000	0.000	.	1.000	0.000
Observations	9,657	9,839	7,006	9,657	9,839	7,006	9,657	9,839	7,006
II. Eligibility from data for top-32 universities									
A. Single-offer model									
COAR graduate	11.579***	16.529***	4.820***	8.566***	13.529***	3.969***	3.012***	3.000***	0.851***
	(0.101)	(0.043)	(0.724)	(0.099)	(0.043)	(0.596)	(0.021)	(0.000)	(0.128)
Control mean	1.597	1.850	0.145	1.187	1.518	0.120	0.409	0.332	0.026
Bandwidth	0.493	0.663	2.494	0.493	0.663	2.494	0.493	0.663	2.494
First-stage F-stat	122.168	168.177	358.364	122.168	168.177	358.364	122.168	168.177	358.364
Observations	2,855	3,838	6,710	2,855	3,838	6,710	2,855	3,838	6,710
B. Multiple-offers model									
COAR graduate	11.630***	16.542***	6.076***	8.624***	13.540***	5.003***	3.006***	3.001***	1.072***
	(0.044)	(0.025)	(0.596)	(0.044)	(0.024)	(0.490)	(0.009)	(0.003)	(0.105)
Control mean	0.732	0.916	0.147	0.555	0.751	0.121	0.178	0.165	0.026
First-stage F-stat	32.348	33.507	29.513	32.348	33.507	29.513	32.348	33.507	29.513
Overid p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.882	1.000	0.000
Observations	9,657	9,839	7,006	9,657	9,839	7,006	9,657	9,839	7,006
III. Eligibility from admission policies for top-32 universities									
A. Single-offer model									
COAR graduate	10.071***	18.000***	5.104***	7.059***	15.000***	4.253***	3.012***	3.000***	0.851***
	(0.093)	(0.000)	(0.767)	(0.092)	(0.000)	(0.639)	(0.021)	(0.000)	(0.128)
Control mean	1.388	1.994	0.154	0.979	1.662	0.128	0.409	0.332	0.026
Bandwidth	0.493	0.663	2.494	0.493	0.663	2.494	0.493	0.663	2.494
First-stage F-stat	122.168	168.177	358.364	122.168	168.177	358.364	122.168	168.177	358.364
Observations	2,855	3,838	6,710	2,855	3,838	6,710	2,855	3,838	6,710
B. Multiple-offers model									
COAR graduate	10.170***	18.007***	6.433***	7.163***	15.006***	5.361***	3.006***	3.001***	1.072***
	(0.045)	(0.015)	(0.631)	(0.045)	(0.013)	(0.525)	(0.009)	(0.003)	(0.105)
Control mean	0.635	0.989	0.156	0.458	0.824	0.130	0.178	0.165	0.026
First-stage F-stat	32.348	33.507	29.513	32.348	33.507	29.513	32.348	33.507	29.513
Overid p-value	0.000	1.000	0.000	0.000	1.000	0.000	0.882	1.000	0.000
Observations	9,657	9,839	7,006	9,657	9,839	7,006	9,657	9,839	7,006

Notes: This table reports 2SLS estimates of COAR graduation on eligibility for extraordinary admissions. Sections I, II, and III report eligibility outcomes for the top-10 universities identified with admission policies, the top-32 universities identified with the data, and the top-32 universities identified with admission policies, respectively. Panels A and B report estimates using the single- and multiple-offers models, respectively. Both models control for baseline math and reading scores. Results for the IB diploma consider whether the university considers IB admissions (eligible) and whether, in addition to being eligible, the applicant has earned the diploma (received). The latter information is not available for the 2017 COAR cohort. Optimal bandwidths are computed following Imbens and Kalyanaraman (2012) with a uniform kernel. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table A.7: Reduced-Form and 2SLS Estimates of IB Diploma

	Exam		Extraordinary		Preparatory		Enrollment
	Application	Admission	Application	Admission	Application	Admission	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I. Private universities							
A. Reduced-form							
IB score = 24	-0.011	-0.030	0.057	0.011	-0.033*	-0.032**	0.034
	(0.045)	(0.040)	(0.047)	(0.043)	(0.020)	(0.016)	(0.048)
Control mean	0.387	0.267	0.444	0.293	0.049	0.031	0.467
Observations	478	478	478	478	478	478	478
RI: p-value	0.838	0.528	0.217	0.828	0.070	0.023	0.500
B. 2SLS							
IB diploma	-0.015	-0.041	0.077	0.015	-0.045*	-0.044**	0.046
	(0.061)	(0.054)	(0.063)	(0.059)	(0.027)	(0.021)	(0.065)
Control mean	0.387	0.267	0.444	0.293	0.049	0.031	0.467
Observations	478	478	478	478	478	478	478
I. Public universities							
A. Reduced-form							
IB score = 24	0.003	0.028	0.033	0.028	0.030	-0.013	0.004
	(0.045)	(0.037)	(0.040)	(0.032)	(0.034)	(0.024)	(0.045)
Control mean	0.676	0.196	0.258	0.124	0.147	0.080	0.413
Observations	478	478	478	478	478	478	478
RI: p-value	1.000	0.441	0.431	0.443	0.400	0.664	1.000
B. 2SLS							
IB diploma	0.004	0.038	0.045	0.037	0.040	-0.017	0.005
	(0.060)	(0.049)	(0.054)	(0.043)	(0.046)	(0.032)	(0.060)
Control mean	0.676	0.196	0.258	0.124	0.147	0.080	0.413
Observations	478	478	478	478	478	478	478

Notes: This table reports reduced form and 2SLS estimates of the IB diploma on college outcomes. The models use whether the student scored 24 vs. 23 points as an instrument for receiving the diploma. Sections I and II report the estimates for private and public universities, and panels A and B report reduced form and 2SLS estimates, respectively. The table also reports randomization inference p-values for the reduced form estimates. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table A.8: Value Added Estimates: List of Controls

	College	Learning
I. Test scores		
2nd-grade secondary math score	X	
2nd-grade secondary reading score	X	
2nd-grade primary math score		X
2nd-grade primary reading score		X
Year 2nd-grade primary eXam was taken		X
II. Socioeconomic variables		
A. Individual		
Socioeconomic index	X	X
Gender	X	X
Attended elementary school	X	X
Repeated grade	X	X
First language	X	X
B. Parent's education		
Highest educational level reached by father	X	X
Highest educational level reached by mother	X	X
C. Dwelling conditions		
Predominant material of walls	X	X
Predominant material of roof	X	X
Predominant material of floor	X	X
Sources of water	X	X
Bathroom characteristics	X	X
Household source of lighting	X	X
D. Household assets		
Radio	X	X
Blender	X	X
Clothing iron	X	X
Television	X	X
Video reproducer	X	X
Telephone	X	X
Mobile phone	X	X
Internet conection	X	X
Desktop computer	X	X
Laptop	X	X
Tablet	X	X
Sound equipment	X	X
Video console	X	X
Microwave	X	X
Fridge	X	X
Washing machine	X	X
Motorcycle	X	X
Car	X	X
III. Additional controls		
A. COAR		
COAR applicant	X	
Region	X	
Cohort	X	
B. SIAGIE		
Repeated 2nd year primary		X
Lagged reading grades (1 year)		X
Lagged math grades (1 year)		X

Notes: This table lists the set of covariates used to estimate SVA models. The controls for test scores and socioeconomic index include a cubic polynomial of these variables. COAR variables are controlled in a flexible manner, such that estimates account for whether students apply to the COAR Network at a specific region-cohort. Missing data is handled by setting missing values to zero and including a missing indicator variable for each variable.

Table A.9: Test for Bias in SVA Models on College Outcomes for Uncontrolled Means

Outcome variable:	Forecast coefficient			Overid test		First-stage
	$\hat{\phi}$	s.e.	$\phi = 1$ p-value	$\chi^2(22)$	p-value	F-stat
	(1)	(2)	(3)	(4)	(5)	(6)
A. Enrollment outcomes						
Any enrollment	0.253	0.088	0.000	21.377	0.498	25.883
Private enrollment	0.594	0.145	0.005	13.522	0.918	27.461
Public enrollment	0.039	0.166	0.000	30.457	0.108	35.818
Top-10 enrollment	0.379	0.133	0.000	18.040	0.704	44.571
Top-10 private enrollment	0.372	0.139	0.000	23.523	0.373	45.705
Top-10 public enrollment	0.481	0.286	0.069	22.572	0.426	16.931
B. Admission outcomes						
Private admission	0.560	0.138	0.001	19.813	0.595	32.451
Public admission	0.038	0.159	0.000	28.465	0.161	34.243
Top-10 private admission	0.657	0.126	0.007	19.285	0.628	49.441
Top-10 public admission	0.391	0.239	0.011	20.638	0.543	16.562
C. Admission modes for private universities						
Exam admission	0.775	0.209	0.281	20.128	0.575	24.573
Extraordinary admission	0.663	0.117	0.004	18.665	0.666	37.563
Exam top-10 admission	1.009	0.197	0.962	32.545	0.069	32.287
Extraordinary top-10 admission	0.610	0.172	0.024	17.863	0.714	48.422
D. Admission modes for public universities						
Exam admission	0.992	0.353	0.981	31.164	0.093	17.865
Extraordinary admission	0.105	0.152	0.000	36.319	0.028	40.242
Exam top-10 admission	1.324	0.642	0.614	36.205	0.029	15.522
Extraordinary top-10 admission	0.533	0.180	0.009	54.085	0.000	25.033

Notes: This table reports the results of tests for bias in school value-added models on college outcomes using the variation from the COAR mechanism in 1st-round COAR school offers and measuring school value added using the high school mean of the outcome. The sample corresponds to students taking the secondary school standardized test in 2015-16, which overlaps with COAR applicants in the 2016-17 application cycles. Column 1 reports the forecast coefficient estimate $\hat{\phi}$ from the 2SLS model in equation 11a, with column 2 reporting the associated robust standard error. Column 3 reports the p-value of the test of the forecast coefficient, ϕ, being equal to 1. Columns 4 and 5 report the over-identification test and the p-value, and column 6 reports the associated first-stage F-statistic of the model in equation 11b. The number of observations for enrollment outcomes in Panel A is 9,400 and for admission outcomes in Panels B, C, and is 9,141.

Table A.10: Tests for Bias in SVA on College Outcomes and Learning due to Unobservables

Outcome:	All sample	Sample with household address in 2017 Census		Households with students in multiple schools	
	OLS	OLS	2SLS	OLS	Household FE
	(1)	(2)	(3)	(4)	(5)
A. Admission modes for private universities					
Exam priv. admission	0.099***	0.099***	0.109***	0.100***	0.088***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.005)
Extra. priv. admission	0.070***	0.071***	0.077***	0.072***	0.062***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Exam top-10 priv. admission	0.026***	0.027***	0.030***	0.026***	0.026***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Extra. top-10 priv. admission	0.025***	0.026***	0.025***	0.027***	0.021***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.003)
Observations	827,701	512,425	512,425	68,347	68,347
B. Admission modes for public universities					
Exam public admission	0.051***	0.052***	0.055***	0.044***	0.043***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Extra. public admission	0.018***	0.019***	0.019***	0.016***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Exam top-10 public admission	0.022***	0.023***	0.021***	0.021***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Extra. top-10 public admission	0.007***	0.008***	0.008***	0.008***	0.010***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)
Observations	827,701	512,425	512,425	68,347	68,347

Notes: This table reports tests for bias in SVA on college admission outcomes by type of university and admission mode due to unobservables. Column 1 reports the OLS estimate of a one-standard-deviation increase in SVA on students' individual outcomes. Columns 2 and 4 report this same estimate for students with the household address in the 2017 Census and for students in households where children attend multiple secondary schools, respectively. Column 3 reports the 2SLS estimate using the SVA of the closest school as an instrument for the SVA of the attended school, and column 5 includes a household fixed effects. Robust standard errors are in parentheses: *significant at 10%, **significant at 5%, ***significant at 1%.

Table A.11: Eligible Schools for Extraordinary Admissions at Top-5 and Top-20 Private Universities vs. Comparable Schools in SVA on Learning, Average Scores, and COAR Schools

Variable:	Top-5 List				Top-20 List			
	Mean (1)	Comp. SVA learning (2)	Comp. av. scores (3)	COAR schools (4)	Mean (5)	Comp. SVA learning (6)	Comp. av. scores (7)	COAR schools (8)
A. Value-added to learning								
SVA math	1.618	0.033	0.065		1.329	0.021	0.118	
	[0.913]	(0.027)	(0.133)		[0.844]	(0.018)	(0.137)	
SVA reading	1.785	-0.004	-0.109		1.489	-0.002	-0.064	
	[0.772]	(0.011)	(0.096)		[0.751]	(0.006)	(0.110)	
SVA total	1.766	0.018	-0.021		1.462	0.013	0.030	
	[0.827]	(0.017)	(0.108)		[0.786]	(0.011)	(0.122)	
B. Average scores								
Av. math score secon. school	1.913	-0.380***	-0.061	1.425***	1.641	-0.464***	-0.086	1.698***
	[0.647]	(0.051)	(0.088)	(0.155)	[0.644]	(0.041)	(0.108)	(0.152)
Av. reading score secon. school	1.927	-0.390***	-0.120	0.571***	1.668	-0.465***	-0.177*	0.830***
	[0.523]	(0.041)	(0.079)	(0.102)	[0.543]	(0.033)	(0.092)	(0.100)
Av. socioeconomic index	1.551	-0.448***	-0.229***	-1.121***	1.433	-0.550***	-0.323***	-1.003***
	[0.244]	(0.048)	(0.054)	(0.069)	[0.292]	(0.040)	(0.059)	(0.069)
C. SVA on college enrollment								
Private enrollment	1.906	-0.647***	-0.333**	-1.082***	1.773	-1.133***	-0.864***	-0.949***
	[0.913]	(0.129)	(0.151)	(0.174)	[0.871]	(0.087)	(0.153)	(0.166)
Public enrollment	-1.040	0.910***	1.004***	0.433	-0.721	0.854***	1.218***	0.115
	[1.250]	(0.188)	(0.292)	(0.274)	[1.202]	(0.122)	(0.231)	(0.263)
Top-10 private enrollment	2.677	-2.172***	-2.080***	0.217	1.983	-2.128***	-2.261***	0.911***
	[2.566]	(0.288)	(0.337)	(0.337)	[2.355]	(0.173)	(0.157)	(0.309)
Top-10 public enrollment	-0.406	0.298*	0.041	-0.205	-0.032	0.254*	-0.373**	-0.579**
	[1.219]	(0.171)	(0.205)	(0.244)	[1.305]	(0.133)	(0.155)	(0.240)
D. SVA on college admissions								
Private admission	1.839	-0.601***	-0.266*	-0.874***	1.719	-1.083***	-0.800***	-0.753***
	[0.860]	(0.124)	(0.142)	(0.196)	[0.833]	(0.086)	(0.149)	(0.190)
Public admission	-0.991	0.808***	0.733***	0.533*	-0.696	0.832***	0.961***	0.238
	[1.359]	(0.189)	(0.216)	(0.275)	[1.250]	(0.122)	(0.165)	(0.262)
Top-10 private admission	2.750	-2.203***	-2.055***	0.253	2.070	-2.237***	-2.341***	0.933**
	[2.404]	(0.298)	(0.332)	(0.395)	[2.239]	(0.185)	(0.156)	(0.375)
Top-10 public admission	-0.414	0.304*	0.019	0.050	-0.073	0.297**	-0.330**	-0.292
	[1.215]	(0.165)	(0.204)	(0.242)	[1.239]	(0.131)	(0.149)	(0.236)
E. SVA on admission modes for private universities								
Exam admission	0.616	0.456***	0.721***	-0.625**	0.989	-0.351***	-0.103	-0.999***
	[1.342]	(0.155)	(0.158)	(0.245)	[1.234]	(0.110)	(0.163)	(0.234)
Extra. admission	2.104	-1.634***	-1.384***	-0.209	1.562	-1.519***	-1.500***	0.334
	[1.738]	(0.204)	(0.240)	(0.442)	[1.605]	(0.129)	(0.163)	(0.430)
Top-10 exam admission	1.296	-0.631*	-0.308	0.150	1.456	-1.660***	-1.546***	-0.010
	[2.762]	(0.378)	(0.382)	(0.580)	[2.641]	(0.234)	(0.202)	(0.565)
Top-10 extra. admission	3.056	-2.935***	-2.912***	1.096**	1.710	-1.816***	-2.073***	2.443***
	[2.616]	(0.239)	(0.262)	(0.509)	[2.359]	(0.165)	(0.131)	(0.489)
F. SVA on admission modes for public universities								
Exam admission	-0.794	0.734***	0.699***	0.009	-0.495	0.740***	0.900***	-0.289
	[1.409]	(0.198)	(0.227)	(0.334)	[1.331]	(0.131)	(0.180)	(0.324)
Extra. admission	-0.664	0.236**	0.179*	1.645***	-0.611	0.360***	0.302***	1.592***
	[0.666]	(0.113)	(0.092)	(0.503)	[0.577]	(0.071)	(0.087)	(0.499)
Top-10 exam admission	-0.283	0.220	0.039	-0.381	0.084	0.208	-0.352**	-0.748***
	[1.394]	(0.166)	(0.228)	(0.278)	[1.417]	(0.134)	(0.166)	(0.272)
Top-10 extra. admission	-0.443	0.121*	0.100	0.646	-0.339	0.160***	0.009	0.543
	[0.474]	(0.070)	(0.078)	(0.681)	[0.566]	(0.057)	(0.067)	(0.679)
Observations	263	405	332	285	562	737	656	584

Notes: This table reports differences between schools eligible for extraordinary admissions at private universities and comparable schools in SVA on learning, average graduates' scores, and COAR schools. Columns 1 to 4 report differences for schools on the list of preferred schools for top-5 private universities and columns 5 to 8 for schools on the list of the top 20. Columns 1 and 5 report the mean for each group, columns 2 and 6 differences with comparable schools in SVA on learning, columns 3 and 7 differences with comparable schools in average scores, and columns 4 and 8 differences with COAR schools. Standard deviations are reported in squared brackets, and robust standard errors in parentheses; *significant at 10%, **significant at 5%, ***significant at 1%.

FIGURE A.1: Universidad del Pacífico: 2021 List of Preferred Schools

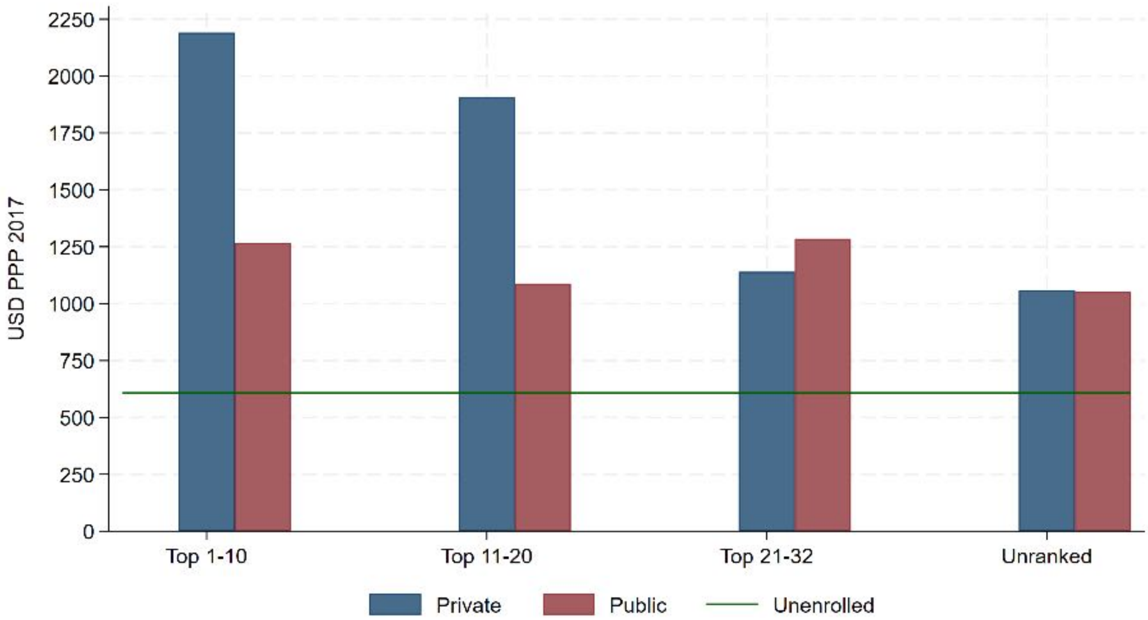
UNIVERSIDAD DEL PACÍFICO

ADMISIÓN 2022

COLEGIO	DIRECCIÓN	DEPARTAMENTO	PROVINCIA	DISTRITO
ALEXANDER VON HUMBOLDT	AV. BENAVIDES 3081	LIMA	LIMA	MIRAFLORES
ALPAMAYO	CL. BUCARAMANGA 145	LIMA	LIMA	ATE
ALTAIR	AV. LA ARBOLEDA 385	LIMA	LIMA	LA MOLINA
AMÉRICA DEL CALLAO	JR. NICOLÁS DE PIÉROLA 250	CALLAO	CALLAO	BELLAVISTA
ANDINO	JR. GUIDO 512	JUNÍN	HUANCAYO	HUANCAYO
ANGLO AMERICANO PRESCOTT	AV. ALFONSO UGARTE 565	AREQUIPA	AREQUIPA	AREQUIPA
ANTONIO RAIMONDI	AV. LA FONTANA 755	LIMA	LIMA	LA MOLINA
CAMBRIDGE COLLEGE LIMA	ALAMEDA DE LOS MOLINOS 728-730	LIMA	LIMA	CHORRILLOS
CEIBOS	AV. BOLOGNESI S/N	LAMBAYEQUE	CHICLAYO	CHICLAYO
CHAMPAGNAT	AV. PASEO DE LA REPÚBLICA 7930-7931	LIMA	LIMA	SANTIAGO DE SURCO
CIENTÍFICO NIVEL A	AV. JAVIER PRADO ESTE 4639	LIMA	LIMA	LA MOLINA
CLARETIANO (JUNÍN)	AV. CENTENARIO 427	JUNÍN	HUANCAYO	HUANCAYO
CLARETIANO (LIMA)	AV. PQUE DE LAS LEYENDAS 555	LIMA	LIMA	SAN MIGUEL
COAR JUNIN	AV. HUAYNA CAPAC S/N	JUNÍN	CHUPACA	CHONGOS BAJO
CRISTO REY	AV. CRISTO REY 450	TACNA	TACNA	TACNA
DE JESÚS	AV. BRASIL 2470	LIMA	LIMA	PUEBLO LIBRE
DE LA CRUZ (LIMA)	CL. ROSA TOLEDO EX SANTA ROSA 224	LIMA	LIMA	PUEBLO LIBRE
DE LA CRUZ (ICA)	CL. TACARACA S/N	ICA	ICA	ICA
DE LA INMACULADA	CL. HERMANO SANTOS GARCÍA 108	LIMA	LIMA	SANTIAGO DE SURCO
DE LA SALLE (AREQUIPA)	AV. LA SALLE 109	AREQUIPA	AREQUIPA	AREQUIPA
DE LOS SAGRADOS CORAZONES BELÉN	AV. ÁLVAREZ CALDERÓN 761	LIMA	LIMA	SAN ISIDRO
FAP JOSÉ ABELARDO QUIÑONES	AUTOPISTA VIA EVITAMIENTO - VILLA FAP S/N	LIMA	LIMA	LA MOLINA
FRANCO PERUANO	AV. MORRO SOLAR 550	LIMA	LIMA	SANTIAGO DE SURCO

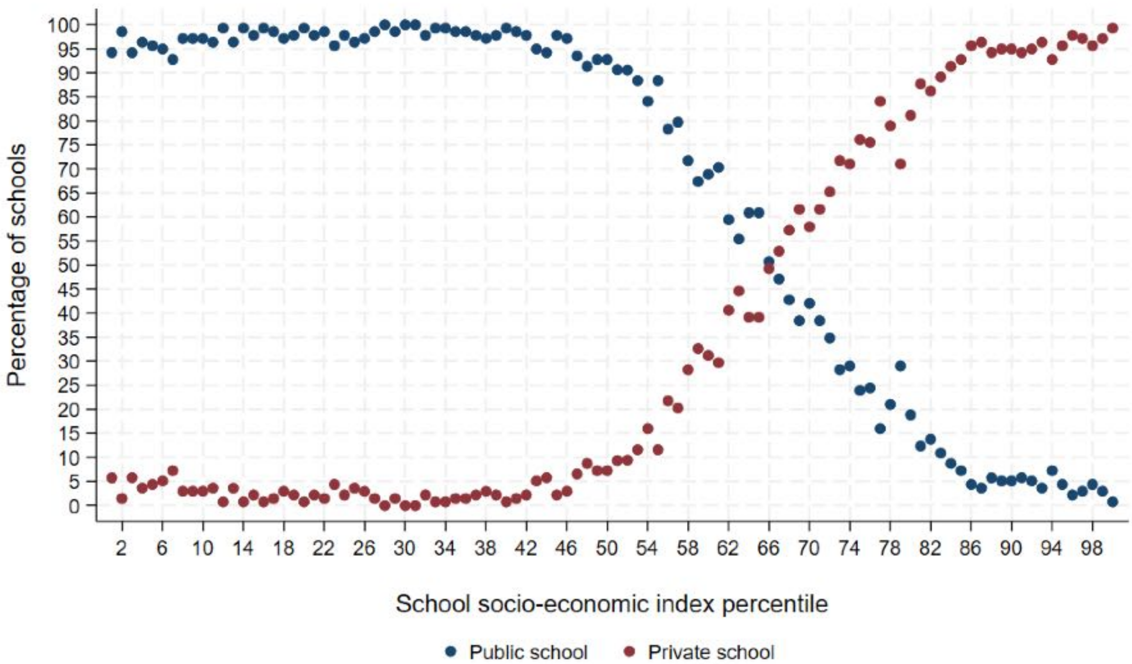
Notes: This figure shows a sample of Universidad del Pacífico's list of preferred schools for its 2022 admission process.

Figure A.2: Monthly Wage by Type of University and Ranking



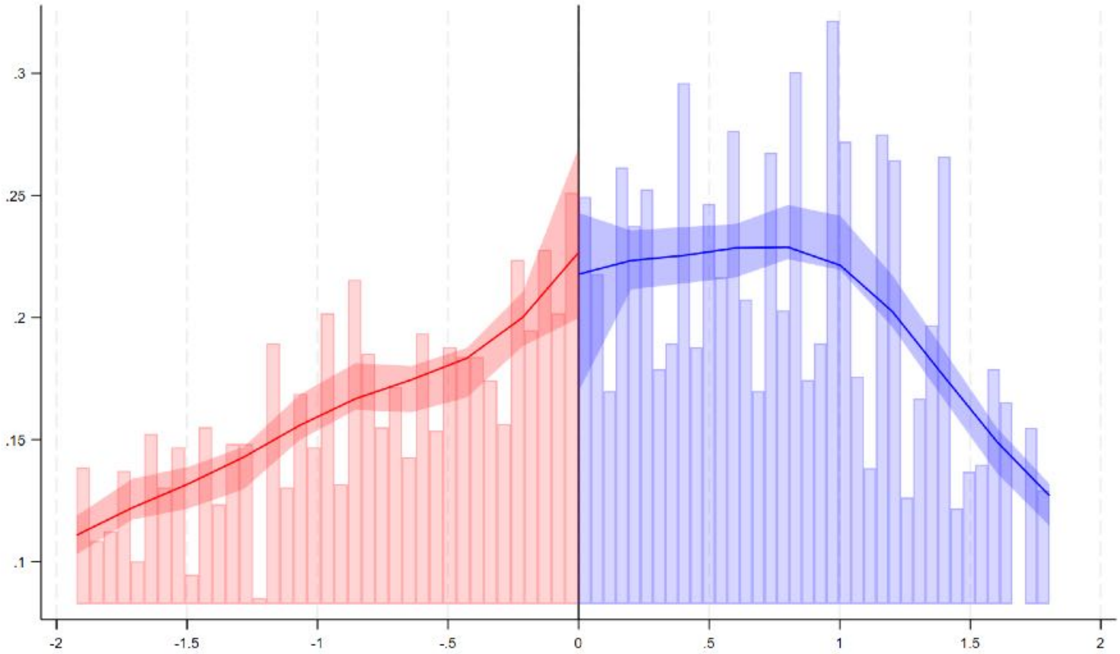
Notes: This figure plots the average monthly wage of graduates in 2019 by type of university and ranking according to a portal designed by the Ministry of Education to provide information about existing programs to college applicants. We use the average wage of high school graduates, as reported by the National Institute of Statistics (INEI), for the "unenrolled" category.

Figure A.3: School Distribution by Average School Socioeconomic Index Percentile



Notes: This figure shows the proportion of private and public schools over the average school socioeconomic index percentile.

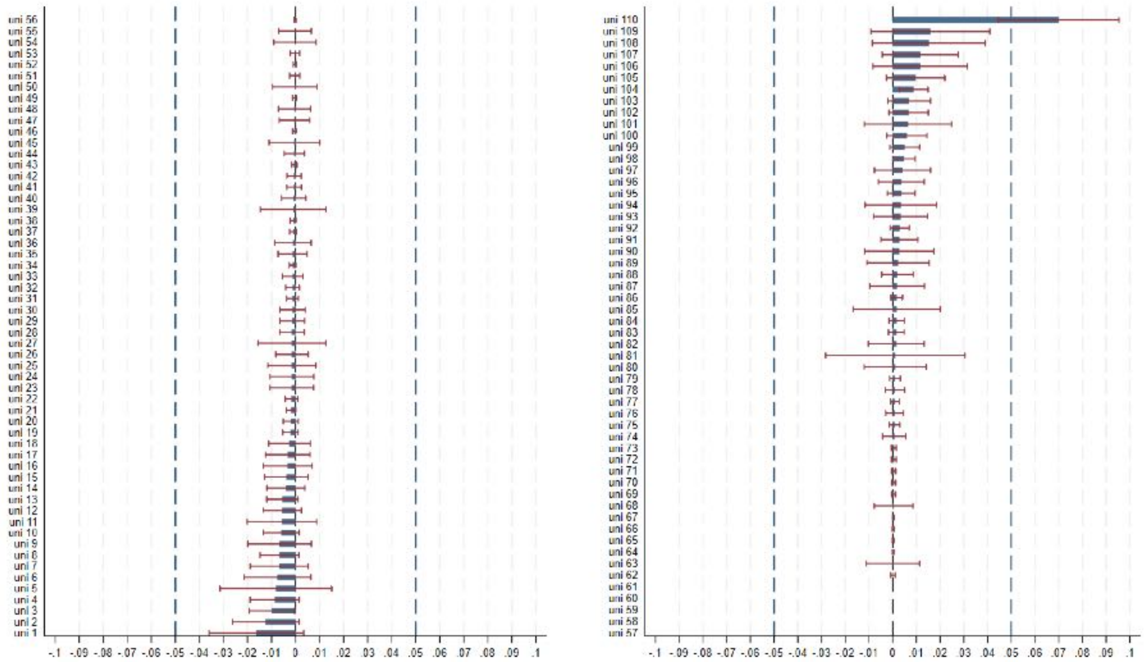
FIGURE A.4: Manipulation Test



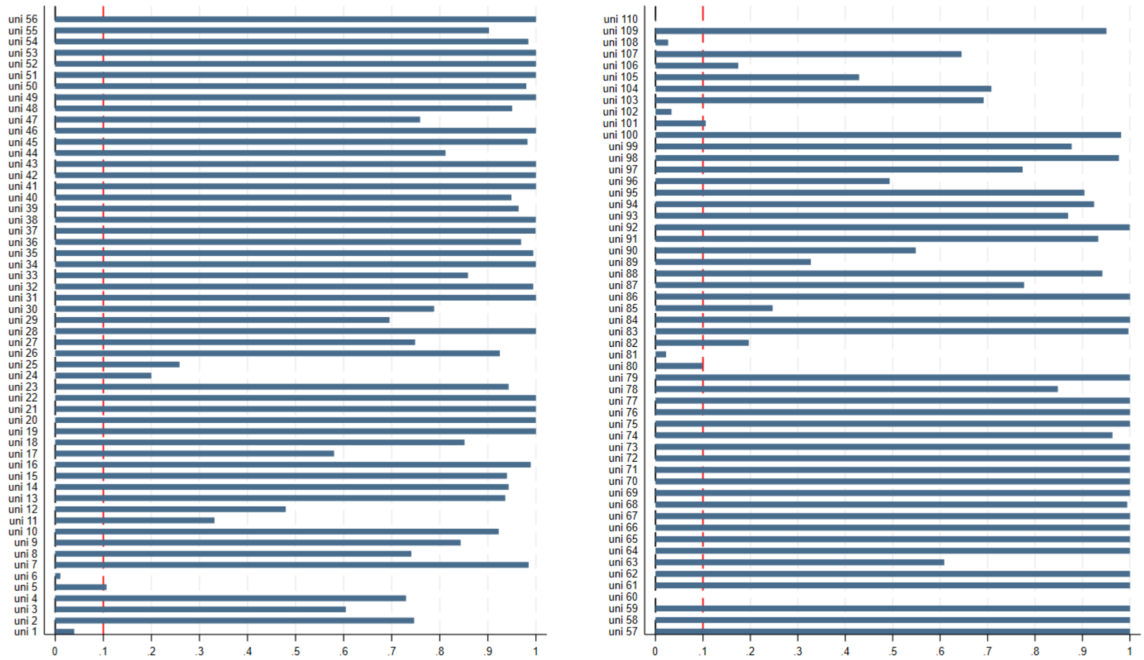
Notes: This figure reports the manipulation test proposed in Cattaneo et al. (2018). The p-value of the manipulation test is 0.277.

Figure A.5: Reduced Form Effects on Having Exam Score for Each University

(A) Single-offer model



(B) Multiple-offers model

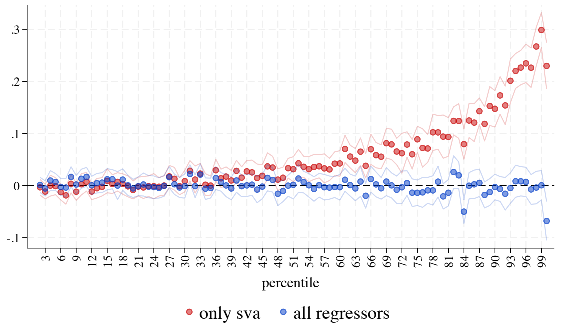


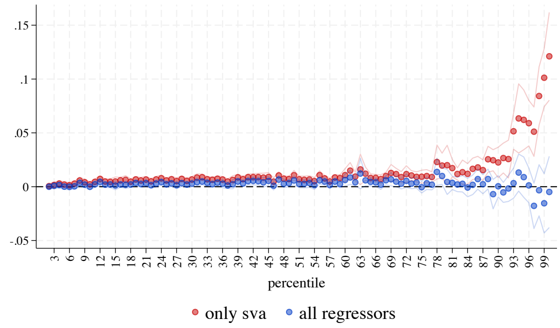
Notes: This figure plots reduced-form effects on the likelihood of COAR applicants having an exam admission score at each university. Panel A reports the reduced form effects of the single-offer model: the effect of clearing the general admission cutoff on the likelihood of having an exam score at each university. Panel B shows selective attrition for the multiple-offers model, reporting the p-value from a joint test of all school-specific COAR offers.

Figure A.6: SVA on College Admissions at Private Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics

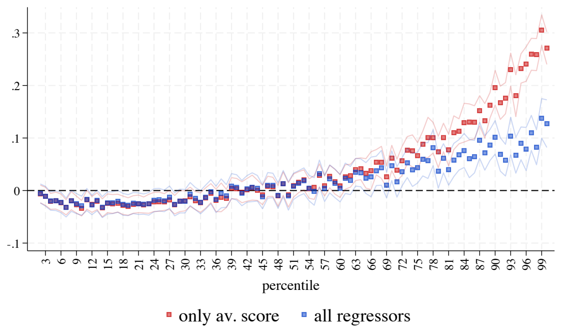
1. All Private Universities | 2. Top-10 Private Universities

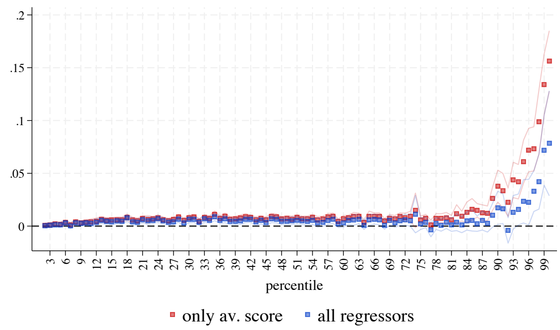
A. SVA on learning



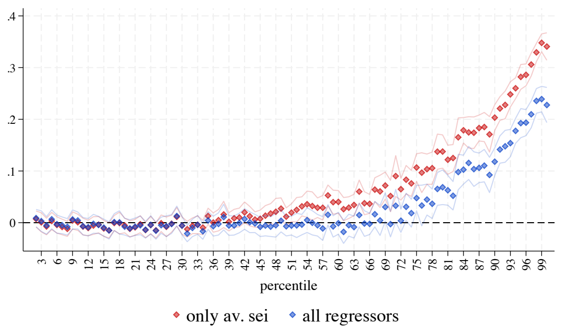


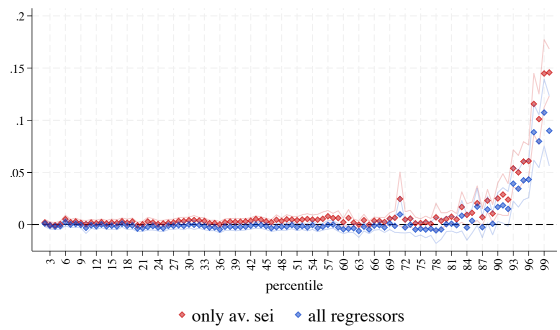
B. Average graduates test scores





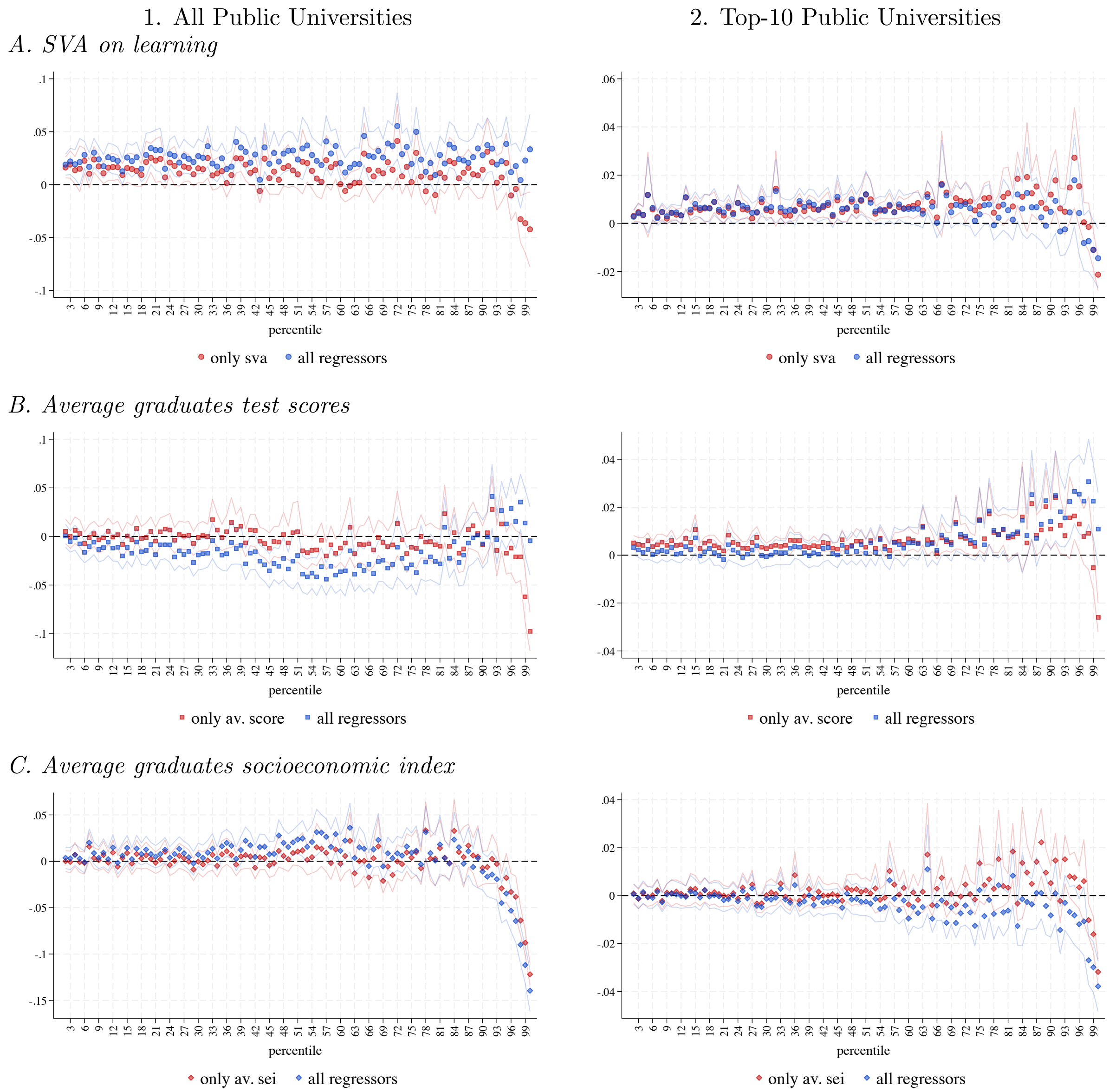
C. Average graduates socioeconomic index





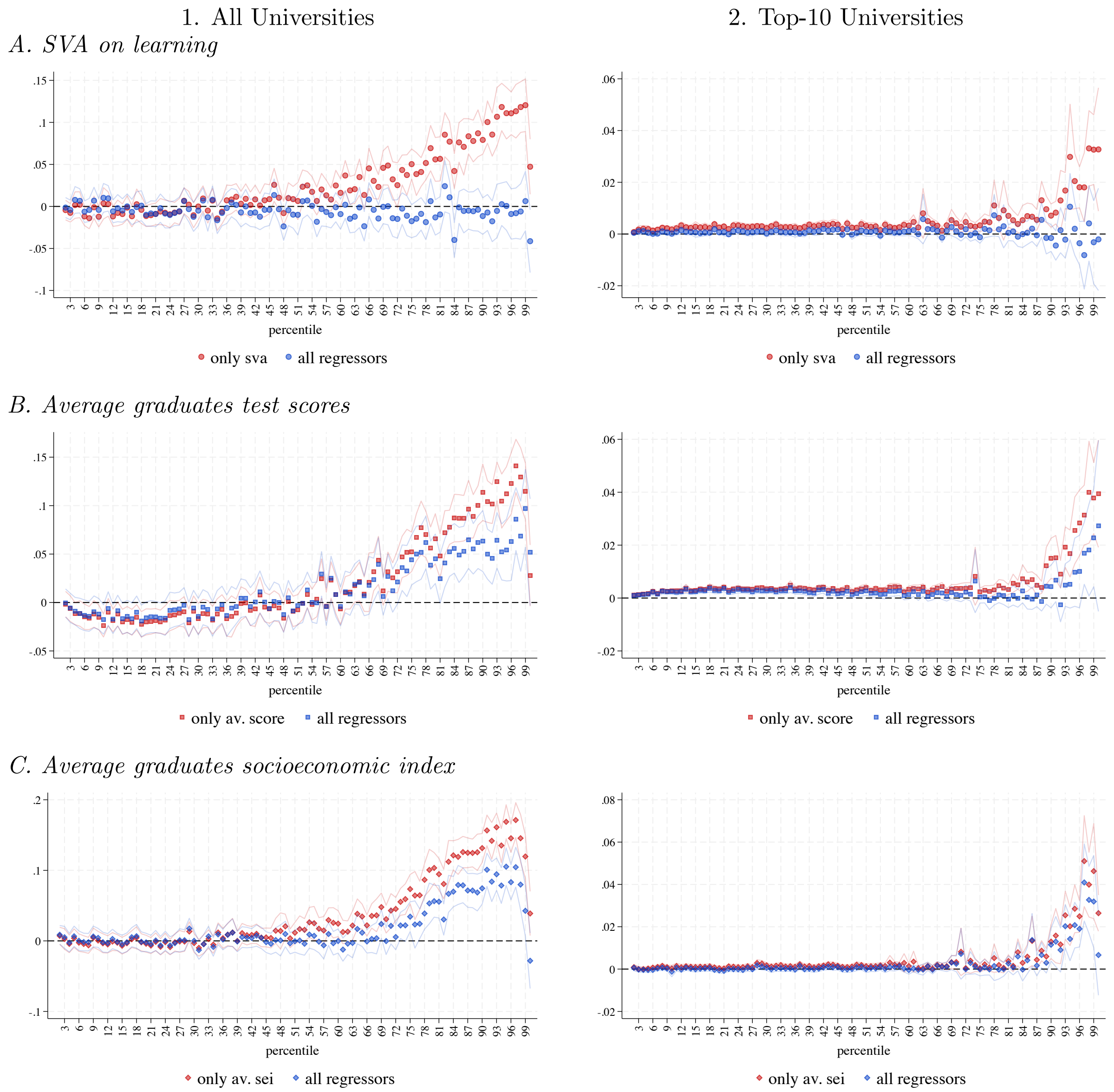
Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college admissions at private universities. Column 1 reports the effects for all private universities, and column 2 for top-10 private universities. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

Figure A.7: SVA on College Admissions at Public Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics



Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college admissions at public universities. Column 1 reports the effects for all public universities, and column 2 for top-10 public universities. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

Figure A.8: SVA on Exam Admissions at Private Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics



Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on exam admissions at private universities. Column 1 reports the effects for all private universities, and column 2 for top-10 private universities. Panel A reports the differences between each percentile and percentile 1 for SVA on learning, and Panels B and C report such differences for average graduates' test scores and the average socioeconomic index, respectively. The red dots correspond to the estimates of models that only include the percentiles of the respective regressor, while the blue dots report the estimates for models that include the percentiles of the three regressors. The figure reports in lines the 95% confidence intervals with robust standard errors.

B Data Appendix

In this appendix, we describe the data used for the analysis, which were provided by the Ministry of Education of Peru. All files can be matched using an administrative unique student identifier and the school code.

B.1 Data sources

B.1.1 COAR Application Files

The COAR application files contain a record for all students who applied to the COAR Network from 2015 to 2017. The files include the applicant's region, the first and second choice of COAR school, the scores from the written exam, the social activity and interview score from the application process, and demographic information such as gender and mother tongue. We standardized scores of the three tests at the cohort level.

The data files also include the first-round offers for the 2016 and 2017 cohorts, but not for the 2015 cohort. We used the assignment algorithm described in section 4.1 to obtain the first-round offers for the 2015 cohort and to identify general and school-specific cutoffs for all cohorts. The first-round offers for the 2016 and 2017 cohorts predicted by the assignment algorithm are identical to the original ones in the data files.

B.1.2 International Baccalaureate (IB) Diploma Program

The IB file contains a record for all COAR Network students who enrolled in the IB program in 2017 and 2018 (who were admitted to the COAR network in the 2015 and 2016 cohorts). The records consist of the final score in the IB and whether the student obtained the diploma.

B.1.3 COAR Students' Cognitive and Non-cognitive Skills

We have COAR students' social networks and socioemotional outcomes to assess balance in academic and non-academic skills. These files come from Zárate (2023), which explores peer effects on social and academic skills within the COAR schools.

B.1.4 School Enrollment Files

These files span the school years from 2013 to 2019 and are sourced from *Sistema de Información de Apoyo a la Gestión de la Institución Educativa* (SIAGIE). Each record includes the attended school, transcripts, and information on whether the student was promoted to the next grade level or held back, dropped out, or required remedial summer classes.

B.1.5 National Standardized Test Files

Data on standardized test scores comes from the *Evaluación Censal de Estudiantes* (ECE). The ECE is a nationwide standardized test taken by students in 2nd grade of primary and secondary school. For primary school, the data covers the 2007-16 period, and for secondary school, it covers the 2015-2019 period, with the exception of 2017 as that year the test was cancelled due to a teacher strike and *El Niño* weather phenomenon. Students from both grade levels were assessed in two subjects: math and reading.

The files include the math and reading scores of all students. Each record also contains information on the student's school and district. For students in 2nd grade of secondary school, the data also includes the responses to a survey conducted during the test that collects information on students' demographics, parental education, household assets, and housing infrastructure, as well as a socioeconomic index constructed by Minedu summarizing this information. We standardized the test scores and the socioeconomic index at the year-subject level.

B.1.6 University Application and Enrollment Files

The college application and enrollment files cover the years 2017 to 2022. The data includes college applications and enrollment information for all students who applied or enrolled at a university during this period. The university application files also include information on the university and major to which the student applied, the application period, the admission mode, admission status and the score in the admission process. The university enrollment files contain information on the student's university, major, and the enrollment period.

We use the 2018 ranking of *The National Superintendency of Higher Education* to classify the top 10 universities in Peru. Table B.1 reports the top 10 universities, whether they are public or private, and their QS World University ranking.

We classify admission modes into three categories: exam admissions, extraordinary admissions, and preparatory academy admissions. Exam admissions correspond to applicants who took the regular admission test. Preparatory academy admissions correspond to whether the applicant was admitted via the university preparatory academy. Finally, extraordinary admissions include the other criteria, such as IB diploma, preferred high school lists, cohort rankings, athletes, and vulnerable and marginalized groups.

We standardize the exam admission scores at the application period, university, and major level. Some universities do not report individual-specific scores for some periods as either the score is missing or it is the same score for all applicants or for all rejected and admitted applicants.

Table B.1: Universities Ranking in Peru

University	Government Ranking	Type	QS World Ranking
Pontificia Universidad Católica del Perú	1	Private	359
Universidad Peruana Cayetano Heredia	2	Private	1001-1200
Universidad Nacional Mayor de San Marcos	3	Public	901-950
Universidad Nacional Agraria La Molina	4	Public	1201-1400
Universidad Nacional de Ingeniería	5	Public	1201-1400
Universidad San Antonio de Abad de Cusco	6	Public	Unranked
Univerisdad Nacional de Trujillo	7	Public	Unranked
Universidad Científica del Sur	8	Private	Unranked
Universidad de Piura	9	Private	1201-1400
Universidad del Pacífico	10	Private	1001-1200

Notes: This table presents the top 10 universities according to *The National Superintendency of Higher Education*, including the type of institution and their position in the QS World University Ranking.

B.1.7 2017 National Census File

We identify students' households and the geographic location of their census blocks from these files. We use this information to validate our school value added measures on learning outcomes.

B.1.8 Schools Census Files

These files span the school years from 2013 through 2019. For each year, this data includes school-level information on total enrollment, number of teachers, and school characteristics, including whether the school is in an urban or rural area and whether it is a private or public institution.

B.2 COAR Sample

In this section, we detailed the construction of the *COAR Sample*. The master file is the COAR applications file comprising 14,019 COAR applicants in 2015 ($N = 3,307$), 2016 ($N = 5,053$), and 2017 ($N = 5,659$). We match these application with the following data sets:

- *School Enrollment:* From this file we obtain school enrollment and transcripts from one year before to three years after COAR applications.
- *National Standardized Tests*: We access information of baseline math and reading test scores, the socioeconomic index, and the graduating peer averages of these variables. This information is available for the 2016 and 2017 cohorts as the test in 2nd grade of secondary school was implemented for the first time in 2015.
- *The School Census File*: From this data we obtain baseline school characteristics for COAR applicants, including the teacher-to-student ratio and whether the school is in an urban or rural area.
- *IB Files*: The IB files allows us to identify the COAR graduates from the 2015 and 2016 cohorts who enrolled at the IB program, their scores, and whether they obtained the diploma.
- *COAR Graduates' Cognitive and Non-Cognitive Skills:* From Zárate (2023), we obtain cognitive and non-cognitive skills of COAR graduates who enrolled in the IB diploma program in the last year of secondary school.
- *University Application and Enrollment:* From this file, we obtain university application and enrollment and exam admission scores within three years after graduating from high school.

Table B.2 reports the matching rates between the COAR applications and the other files by cohort, as well as the availability of each variable in each file.

Table B.2: Matching Rates: COAR Application File vs Other Files (%)

	Matching rate (%)		
	2015	2016	2017
A. Secondary school enrollment			
2nd-grade enrollment	99.94	99.98	100.00
3rd-grade enrollment	100.00	99.98	99.96
5th-grade enrollment	99.64	99.51	99.70
B. 2nd-grade secondary school transcripts			
Math	99.94	99.98	100.00
Literature	99.94	99.98	100.00
History and Geography	99.94	99.98	100.00
Science and Technology	99.94	99.98	100.00
English	99.94	99.98	100.00
C. 2nd-grade secondary national standardized test			
Math	0.00	98.87	99.38
Reading	0.00	98.87	99.38
Socioeconomic index	0.00	98.38	99.19
D. Education census			
Urban school	99.94	99.98	99.98
Student-teacher ratio	99.94	99.98	99.98
E. University enrollment and application			
University application	90.41	89.83	92.08
University enrollment	77.32	73.36	78.18
F. IB diploma program			
Enrolled in the IB program	72.98	74.43	0.00
G. COAR graduates' cognitive and non-cognitive skills			
Centrality Social Network	99.91	99.87	0.00
Total Degree Social Network	100.00	99.94	0.00
Leadership: Peer perception	100.00	100.00	0.00
Leadership: Own perception	96.13	95.63	0.00
Grit	96.04	94.81	0.00
Empathy	91.52	92.91	0.00
Happiness	91.52	92.91	0.00
Family Support	91.52	92.91	0.00
Total Stress	91.52	92.91	0.00
Reading	99.72	100.00	0.00
Math	99.72	100.00	0.00
Cognitive	100.00	100.00	0.00

Notes: This table reports the matching rates between the COAR application file and the remaining files. Matching rates in Panels A to E are calculated as percentages of COAR applicants. In contrast, matching rates in Panel F are calculated as a percentage of COAR graduates and in Panel G as percentages of COAR graduates who enrolled in the IB diploma program.

B.3 All Schools Sample

In this section, we detailed the construction of the *All Schools Sample*. The master file is the 2nd-grade secondary national standardized test consisting of 2,022,202 students who took the test in 2015 ($N = 489,780$), 2016 ($N = 502,521$), 2018 ($N = 521,570$), and 2019 ($N = 508,331$).

We match these files with the following data sets:

- *School Enrollment:* From this file, we obtain school enrollment and transcripts two years and one year before taking the test (2015-2019 test takers) and school enrollment three years after taking the test (2015-2016 test takers).
- *Past Standardized Tests:* From this data, we obtain math and reading test scores in 2nd grade of primary school.
- *The School Census File:* We access information on the school district and whether the school is private or public three years after taking the test.
- *National Census:* The national census allows us to access information on the blocks where the test takers resided in 2017 and their geolocation (latitude and longitude).
- *University Application and Enrollment:* From this file, we obtain university application and enrollment within three years after taking the test of the 2015 and 2016 test takers.

Table B.3 reports the matching rates between the national standardized tests in 2nd grade of secondary school and the other files by year, as well as the availability of each variable in each file.

TABLE B.3: Matching Rates: National Standardized Test vs Other Files (%)

	Matching rate (%)			
	2015	2016	2018	2019
A. School enrollment				
Two years before taking the test	98.51	98.71	98.86	98.19
One year before taking the test	99.17	99.32	99.19	98.80
Three years after taking the test	90.14	90.88	0.00	0.00
B. Transcripts one year before taking the test				
Math	98.74	98.99	98.90	98.29
Literature	98.74	98.99	98.90	98.29
C. 2nd-grade primary national standardized test				
2nd-grade primary math score	78.55	81.96	85.20	86.51
2nd-grade primary reading score	78.42	81.98	85.23	86.54
D. Education Census				
School district	90.12	90.78	0.00	0.00
Type of institution	90.12	90.78	0.00	0.00
E. National census				
Broadbloack	75.77	75.78	75.90	74.35
Broackblock's location	75.57	75.59	75.72	74.16
F. University enrollment and application				
University enrollment	33.18	33.58	0.00	0.00
University enrollment	45.15	45.84	0.00	0.00

Notes: This table reports the matching rates between the National Standardized Test file and the remaining files by year.

C COAR Assignment Mechanism

This appendix describes the COAR assignment mechanism and characterizes the vector of propensity scores. Each applicant in the mechanism is defined by their type, which is a combination of their region and their first and second choices, denoted as $\theta_i = (l_i, c_{1_i}, c_{2_i})$. Additionally, each applicant has an admission score r_i. Without loss of generality, we assume that the running variable r_i is distributed over the interval $[0, \overline{R}]$ with $\overline{R} < \infty$.

C.1 Steps of the Assignment Mechanism

Step 1: Assignment of 1st-round any COAR offers

In the first step, the government assigns slots for any COAR offers by determining the number of total slots available to each region. Let $\tilde{q}_l$ denote the number of slots assigned to region l, with $Q = \sum\limits_{l \in \mathcal{L}} \tilde{q}_l$. Applicants are ranked within their region of origin with the score of the marginal applicant at $\tilde{q}_l$ generating the general COAR qualifying cutoff, $\tau_0(l_i)$, as a function of applicant's region of origin l_i. The any-COAR offer, D_i, is then determined by this cutoff as follows:

$$D_i = \begin{cases} 0 & \text{if } r_i < \tau_0(l_i), \\ 1 & \text{if } r_i \geq \tau_0(l_i). \end{cases} \tag{C.1}$$

Only applicants that surpass this general regional-specific quota receive an offer to join any COAR school. The specific school from which they receive a first-round offer is determined in Step 2. For those that do not surpass this cutoff the mechanism assigns them to a traditional public school: if $r_i < \tau_0(l_i)$, then $\mu(i) = 0$.

Step 2: Assignment of 1st-round school-specific offers

In the second step, the government assigns school-specific offers. For this assignment, the government only considers applicants who are eligible to receive a general COAR offer according to step 1 ($D_i = 1$). For each applicant, the mechanism generates two additional relevant cutoffs: $\tau_1(i)$ that determines an offer from the 1st-choice school vs. the 2nd-choice, and $\tau_2(i)$ which determines an offer from the 2nd-choice vs. a "pending" COAR offer.

Step 2.1.: 1st-choice offers

The government first assigns applicants to their 1st-choice offers. For this assignment, the mechanism differentiates applicants from regions with a COAR school and applicants from other regions, with the former group being assigned first. Let w_i denote a variable indicating whether the applicant's regions has a COAR school: $w_i = 1$ if $l_i \leq S$ and 0, otherwise.

Step 2.1.1: 1st-choice offers for applicants from regions with a COAR school

For the slots available at each COAR school s, the government determines a same-region quota that prioritizes students applying from the school's region. Let m_s denote the slots allocated to applicants from the same region at school s and o_s denote slots allocated to applicants from other regions, with $q_s = m_s + o_s$ and $m_s < q_s$.

Applicants from region with an exam school $l_i \leq S$ are ranked by r_i within their region with the marginal applicant at position m_s determining the cutoff $\tau_1(l_i)$ for first-choice offers of applicants from region l_i. Due to the restrictions on applicants preferences, as the region of origin coincides with the 1st-choice of the applicants ($l_i = c_{1_i}$), τ_1 can also be expressed as a function of c_{1_i} and the indicator variable w_i to exclude applicants from regions without a COAR school who would face a different cutoff: $\tau_1(l_i) = \tau_1(w_i, c_{1_i})$ for $l_i \leq S$.

Step 2.1.2: 1st-choice offers for applicants from regions without a COAR school

After assigning same-region slots, the mechanism considers applicants from regions without a COAR school ($l_i > S$) to their first choice. Applicants are grouped by their 1st-choice c_{1i} and ranked by the admission score r_i. The score of the marginal applicant at seat o_s determines the cutoffs $\tau_1(w_i, c_{1_i})$ that denote the threshold determining 1st-choice offers for this set of applicants. As before, this threshold is a function of whether the region has a COAR school, as applicants from the other regions are treated equally, and the first choice c_{1_i}, as such applicants are ranked within their first choice.

Applicants from regions with and without a COAR school receive a 1st-choice offer if their admission score is above their specific cutoff: if $r_i \geq \tau_1(w_i, c_{1_i})$, then $\mu(i) = c_{1i}$. Applicants who do not clear this threshold are rejected from their first choice and will be assigned either to their second choice or a "pending" offer in step 2.2.

Step 2.2: 2nd-choice offers

Rejected applicants in steps 2.1. are then grouped by their second choice, regardless of their region of origin and their first choice. Let v_s denote the number of remaining seats at school s: $v_s = q_s - |i \in \mathcal{I} : \; c_{1i} = s, \; r_i \geq \tau_1(w_i, s)|$. The score of the marginal applicant with $c_{2_i} = s$ at position v_s generates the cutoff $\tau_2(c_{2_i})$, which determines the 2nd-choice offers. As rejected applicants in step 2.1. are grouped by their second choice, this cutoff is a function of c_{2_i}.

Rejected applicants in step 2.1. receive an offer from their second choice if their admission score is above the cutoff $\tau_2(c_{2_i})$: if $r_i \geq \tau_2(c_{2_i})$, then $\mu(i) = c_{2_i}$. Applicants who do not clear this threshold are rejected from their 2nd-choice and are assigned to a pending COAR school, denoted by p. This step ends the process of 1st-round offers, which is the one we leverage in our empirical design.

The 1st-round allocation for applicant i of type $\theta_i = (l_i, c_{1_i}, c_{2_i})$ and admission score r_i can be summarized as follows:

$$\mu(i) = \begin{cases} 0 & \text{if } r_i < \tau_0(l_i), \\ c_{1_i} & \text{if } \tau_0(l_i) \leq r_i \text{ and } \tau_1(w_i, c_{1_i}) \leq r_i, \\ c_{2_i} & \text{if } \tau_0(l_i) \leq r_i \text{ and } \tau_2(c_{2_i}) \leq r_i < \tau_1(w_i, c_{1_i}), \\ p & \text{if } \tau_0(l_i) \leq r_i \text{ and } r_i < \tau_1(w_i, c_{1_i}) \text{ and } r_i < \tau_2(c_{2_i}). \end{cases} \tag{C.2}$$

In some cases, applicants' second choice may be undersubscribed at stage 2.2, allowing all of them to receive a second-choice offer. The matching function accounts for such scenarios by setting the relevant cutoff to 0. Additionally, when there are no longer available seats, the relevant cutoff is ∞. For example, there may be no seats available for an applicant's second choice if all other-region slots are assigned as first-choice offers to applicants from other regions. In such cases, $\tau_2(c_{2_i})$ is equal to ∞.

Step 3: Assignment of 2nd-round offers

While we do not use second-round offers in out research design, the process works as follows. The government ranks applicants with a pending offer, and, following this ranking, call the applicant's families offering the available COAR slots. The applicant can either accept or reject this offer. A rejection implies staying in a traditional public school. If there are still slots after calling all eligible candidates in Step 1, the government ranks all rejected applicants by r_i and perform the same process. The matching ends when there are no longer seats available or when all remaining applicants have rejected the available seats.

C.2 Propensity Scores

This section derives the vector of propensity scores, the conditional probability of receiving an offer from each school s for all schools $s \in COAR$ for the COAR Assignment Mechanism. Following Abdulkadiroğlu et al. (2017b), assume that the running variable r_i is distributed over $[0, \overline{R}]$ with continuously differentiable cumulative distribution F^i, where running variables are independent for $i \neq j$, but not necessarily identically distributed. For instance, in our case, the observed value of the running variable can be drawn from the distribution generated by retesting applicant i in the three admission tests for the COAR Network. Let $F_x(R)$ denote the cumulative probability that a set of applicants with shared characteristic x have a tie-breaker below any value R, where $F_x(R) = \mathbb{E}\left[F^i(R)|x_i = x\right]$ and $F^i(R)$ is F^i evaluated at R.

The COAR mechanism derives into three cutoffs for each applicant: τ_0, τ_1, and τ_2, that determine allocation to any COAR school and specific schools. For each cutoff, τ_j, define an interval $[\tau_j - \delta_j, \tau_j + \delta_j]$ for $j \in \{0, 1, 2\}$, where the parameter δ_j is a bandwidth analogous to the one used for non-parametric RD estimation. As in Abdulkadiroğlu et al. (2022), the local propensity score (the value of the conditional probability of a school offer when $\delta_j \to 0$ for $j \in \{0, 1, 2\}$) treats the qualification status of applicants inside the interval as randomly assigned, which is justified by the fact that, given the continuous differentiability of the admission score distribution, the admission score distribution inside the bandwidth limits to a uniform distribution as the bandwidth shrinks to zero.

To characterize the propensity score for each school s, let's first characterize an applicant's propensity score of receiving an offer from any school in the COAR Network, denoted by π_i. Note that this propensity score is determined by the cutoff $\tau_0(l_i)$ and the size of bandwidth δ_0 around this cutoff. In particular, as all applicants who clear this cutoff by a large margin, $r_i > \tau_0(l_i) + \delta_0$ will receive a COAR offer, their propensity score π_i is equal to 1. Analogously, applicant's whose score falls below this cutoff by a large margin, $r_i < \tau_0(l_i) - \delta_0$ will never receive a COAR offer and hence π_i will be equal to 0. For applicant's inside the bandwidth, $|r_i - \tau_0(l_i)| \leq \delta_0$, only the proportion who clear the admission cutoff receive an offer. Hence, the propensity score of receiving any COAR offer is given by:

$$\pi_i = \mathbb{E}\left[D_i = 1|\theta_i = \theta\right] = \begin{cases} 0 & \text{if} \quad r_i < \tau_0(l_i) - \delta_0 \\ \frac{F_l(\tau_0+\delta_0)-F_l(\tau_0)}{F_l(\tau_0+\delta_0)-F_l(\tau_0-\delta_0)} & \text{if} \quad |r_i - \tau_0(l_i)| \leq \delta_0, \\ 1 & \text{if} \quad r_i > \tau_0(l_i) + \delta_0. \end{cases} \tag{C.3}$$

We can characterize the local propensity score by calculating the limit of the expression in equation C.3 when $\delta_0 \to 0$. By using L'Hôpital's rule we have that the expression in the middle of equation C.3 limits to:

$$\lim_{\delta_0 \to 0} \frac{F_l(\tau_0+\delta_0) - F_l(\tau_0)}{F_l(\tau_0+\delta_0) - F_l(\tau_0-\delta_0)} = \lim_{\delta_0 \to 0} \frac{F_l'(\tau_0+\delta_0)}{F_l'(\tau_0+\delta_0) + F_l'(\tau_0-\delta_0)} = \frac{F_l'(\tau_0)}{2F_l'(\tau_0)} = 0.5,$$

which implies that:

$$\lim_{\delta_0 \to 0} \pi_i = \begin{cases} 0 & \text{if} \quad r_i < \tau_0(l) - \delta_0, \\ 0.5 & \text{if} \quad |r_i - \tau_0(l)| \leq \delta_0, \\ 1 & \text{if} \quad r_i > \tau_0(l) + \delta_0. \end{cases} \tag{C.4}$$

To characterize the propensity score for each school s, first notice that a general COAR offer, D_i, has to equal to the sum of school specific offers across all COAR schools and a pending offer $s = p$. Likewise, the propensity score of receiving an offer from any COAR school has to equal the sum of propensity scores across all schools in the network and a pending offer. Hence, we must have that:

$$D_i = \sum_{s \in COAR} D_{s,i},$$
$$\pi_i = \sum_{s \in COAR} \pi_{s,i},$$

where $D_{s,i}$ denotes a school-specific offer, and $\pi_{s,i} = \mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta\right]$ denotes the propensity score of receiving an offer from school s, where $s \in COAR$ also include a pending offer, $s = p$.

By the law of total probability we also have that:

$$\begin{aligned} \pi_{s,i} = \mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta\right] = \quad & \mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta, D_i = 1\right] \times \pi_i + \\ & \mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta, D_i = 0\right] \times (1 - \pi_i). \end{aligned}$$

Note that by properties of the assignment mechanism, an applicant will never receive an offer from a specific school when they do not receive a general COAR offer. This implies that as $\mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta, D_i = 0\right] = 0$, then:

$$\pi_{s,i} = \tilde{\pi}_{s,i} \times \pi_i, \tag{C.5}$$

with $\tilde{\pi}_{s,i}$ denoting $\mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta, D_i = 1\right]$: the probability of receiving a specific school offer conditional on receiving a general COAR offer.

We first characterize $\tilde{\pi}_{s,i}$ when s is the first choice of the applicant ($c_{1_i} = s$). In this case, the relevant variation that determines this conditional probability is determined by bandwidth δ_1 around cutoff τ_1. Conditional on receiving a general COAR offer, as all applicants who clear cutoff τ_1 by a large margin $r_i > \tau_1(w_i, c_{1_i}) + \delta_1$ receive an offer from their first choice, their conditional propensity score for school s is equal to 1. Likewise, conditional on a general COAR offer, applicants who do not clear cutoff τ_1 by a large margin, never receive an offer from their first choice, and hence, their conditional propensity score is equal to 0. For applicants inside the bandwidth, $|r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1$, only the proportion who clear the admission cutoff receive an offer. Hence, we have that:

$$\tilde{\pi}_{c_{1_i},i} = \begin{cases} 0 & \text{if} \quad r_i < \tau_1(w_i, c_{1_i}) - \delta_1, \\ \frac{F_{w,c_1}(\tau_1+\delta_1)-F_{w,c_1}(\tau_1)}{F_{w,c_1}(\tau_1+\delta_1)-F_{w,c_1}(\tau_1-\delta_1)} & \text{if} \quad |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1, \\ 1 & \text{if} \quad r_i > \tau_1(w_i, c_{1_i}) + \delta_1. \end{cases} \tag{C.6}$$

As for equation C.3, we can applying L'Hôpital's rule to the middle expression and we have that:

$$\lim_{\delta_1 \to 0} \tilde{\pi}_{c_{1_i},i} = \begin{cases} 0 & \text{if} \quad r_i < \tau_1(w_i, c_{1_i}) - \delta_1, \\ 0.5 & \text{if} \quad |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1, \\ 1 & \text{if} \quad r_i > \tau_1(w_i, c_{1_i}) + \delta_1. \end{cases} \tag{C.7}$$

Next, we characterize the propensity score when s is the second choice of the applicant and conditional on receiving a general COAR offer, $D_i = 1$. In such a case, applicants have a non-degenerate risk of receiving an offer from school s when they are either in the bandwidth around cutoff τ_1 or in the bandwidth around cutoff τ_2. In particular, applicants who with probability 1 receive an offer from their 1st choice ($r_i > \tau_1(w_i, c_{1_i}) + \delta_1$) will never receive an offer from their second choice. By contrast, applicants who face a non-degenerate risk of receiving an offer from their first choice, also face a non-degenerate risk of receiving an offer from their second choice, as this is the relevant counterfactual offer around the τ_1 cutoff. Likewise, applicants within the bandwidth around cutoff τ_2 ($|r_i - \tau_2(c_{2_i})| < \delta_2$), also face a non-degenerate risk of receiving an offer from their second choice, while applicants further below this cutoff never receiving an offer from their second choice, and hence having a propensity score equal to zero. The propensity score of receiving an offer from their second choice can then be summarized as:

$$\tilde{\pi}_{c_{2_i},i} = \begin{cases} 0 & \text{if} & \begin{array}{l} r_i > \tau_1(w_i, c_{1_i}) + \delta_1 \quad \text{or} \\ r_i < \tau_2(c_{2_i}) - \delta_2, \end{array} \\ \begin{array}{l} \frac{F_{w,c_1,c_2}(\tau_1)-F_{w,c_1,c_2}(\tau_1-\delta_1)}{F_{w,c_1,c_2}(\tau_1+\delta_1)-F_{w,c_1,c_2}(\tau_1-\delta_1)} \\ \times \frac{F_{c_2}(\tau_2+\delta_2)-F_{c_2}(\tau_2)}{F_{c_2}(\tau_2+\delta_2)-F_{c_2}(\tau_2-\delta_2)} \end{array} & \text{if} & \begin{array}{l} |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \quad \text{and} \\ |r_i - \tau_2(c_{2_i})| \leq \delta_2, \end{array} \\ \frac{F_{w,c_1,c_2}(\tau_1)-F_{w,c_1,c_2}(\tau_1-\delta_1)}{F_{w,c_1,c_2}(\tau_1+\delta_1)-F_{w,c_1,c_2}(\tau_1-\delta_1)} & \text{if} & \begin{array}{l} |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \quad \text{and} \\ r_i - \tau_2(c_{2_i}) > \delta_2, \end{array} \\ \frac{F_{c_2}(\tau_2+\delta_2)-F_{c_2}(\tau_2)}{F_{c_2}(\tau_2+\delta_2)-F_{c_2}(\tau_2-\delta_2)} & \text{if} & \begin{array}{l} r_i - \tau_1(w_i, c_{1_i}) < \delta_1 \quad \text{and} \\ |r_i - \tau_2(c_{2_i})| \leq \delta_2, \end{array} \\ 1 & \text{if} & \begin{array}{l} r_i < \tau_1(w_i, c_{1_i}) - \delta_1 \quad \text{and} \\ r_i > \tau_2 + \delta_2, \end{array} \end{cases} \tag{C.8}$$

with the local propensity score equal to $\lim\limits_{(\delta_1,\delta_2)\to(0,0)} \mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta, c_{2_i} = s, D_i = 1\right]$.

To characterize this local propensity score we use the fact that for $h(x,y) = \frac{f(x,y)}{g(x,y)}$ with $f(x,y) = f_x(x) \cdot f_y(y)$ and $g(x,y) = g_x(x) \cdot g_y(y)$, we have that if $\underset{x\to 0}{lim} \frac{f_x(x)}{g_x(x)}$ and $\underset{y\to 0}{lim} \frac{f_y(y)}{g_y(y)}$ exist then:

$$\lim_{(x,y)\to(0,0)} \frac{f(x,y)}{(g(x,y))} = \lim_{(x,y)\to(0,0)} \frac{f_x(x)}{g_x(x)} \frac{f_y(y)}{g_y(y)} = \lim_{x\to 0} \frac{f_x(x)}{g_x(x)} \lim_{y\to 0} \frac{f_y(y)}{g_y(y)}. \tag{C.9}$$

Using C.9 and by applying L'Hôpital's to the three middle lines of the propensity score derived in equation C.8, and as $F_x(r_i)$ is continuously differentiable, we have that:

$$\lim_{(\delta_1,\delta_2)\to(0,0)} \tilde{\pi}_{c_{2_i},i} = \begin{cases} 0 & \text{if} \quad \begin{array}{l} r_i > \tau_1(w_i, c_{1_i}) + \delta_1 \quad \text{or} \\ r_i < \tau_2(c_{2_i}) - \delta_2, \end{array} \\ 0.25 & \text{if} \quad \begin{array}{l} |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \quad \text{and} \\ |r_i - \tau_2(c_{2_i})| \leq \delta_2, \end{array} \\ 0.5 & \text{if} \quad \begin{array}{l} |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \quad \text{and} \\ r_i - \tau_2(c_{2_i}) > \delta_2, \end{array} \\ 0.5 & \text{if} \quad \begin{array}{l} r_i - \tau_1(w_i, c_{1_i}) < \delta_1 \quad \text{and} \\ |r_i - \tau_2(c_{2_i})| \leq \delta_2, \end{array} \\ 1 & \text{if} \quad \begin{array}{l} r_i < \tau_1(w_i, c_{1_i}) - \delta_1 \quad \text{and} \\ r_i > \tau_2 + \delta_1. \end{array} \end{cases} \tag{C.10}$$

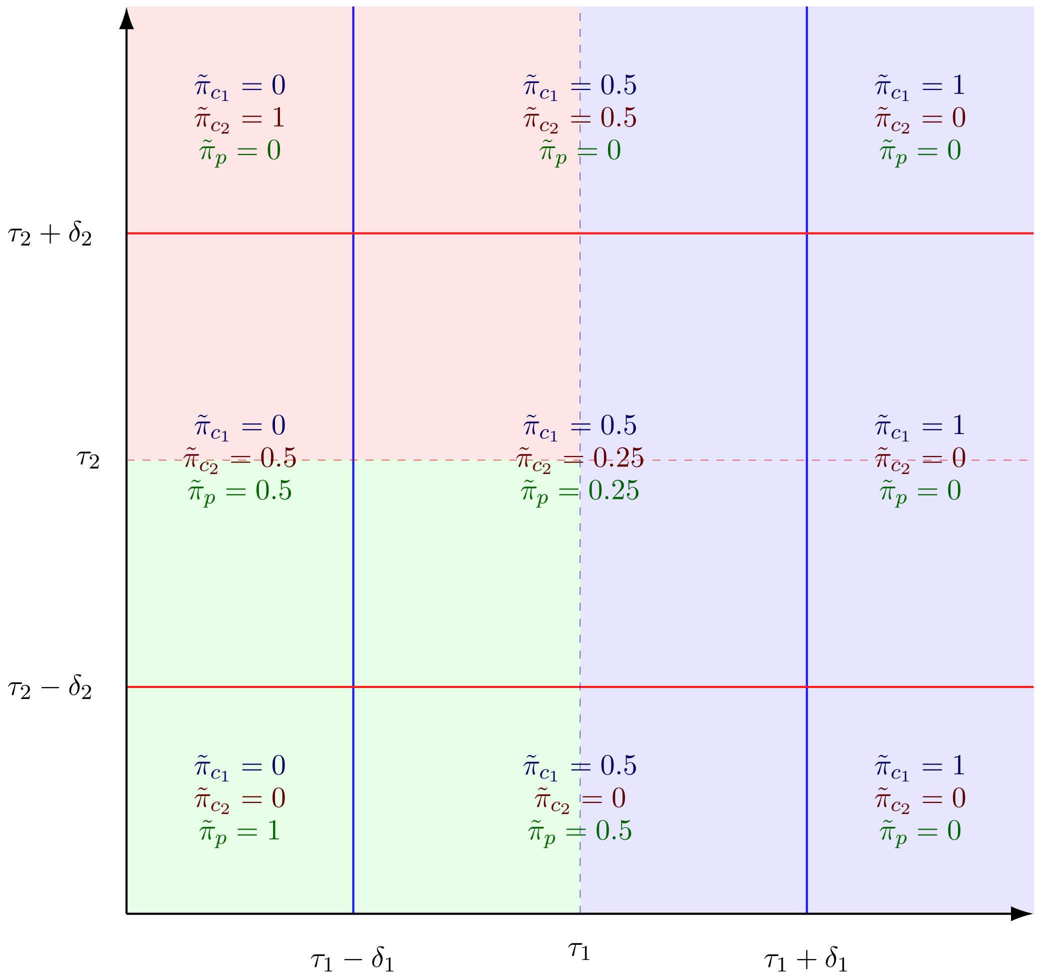
Finally, we characterize the propensity score of receiving a pending offer, $s = p$, conditional on receiving an offer from any COAR school, $D_i = 1$. Given, the order of the assignment mechanism, the relevant counterfactual for a pending offer can be characterized as follows:

$$\tilde{\pi}_{p,i} = \begin{cases} 0 & \text{if} \quad \begin{array}{l} r_i > \tau_1(w_i, c_{1_i}) + \delta_1 \quad \text{or} \\ r_i > \tau_2(c_{2_i}) + \delta_2, \end{array} \\ \frac{F_{w,c_1}(\tau_1) - F_{w,c_1}(\tau_1 - \delta_1)}{F_{w,c_1}(\tau_1 + \delta_1) - F_{w,c_1}(\tau_1 - \delta_1)} & \text{if} \quad \begin{array}{l} |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \quad \text{and} \\ r_i < \tau_2(c_{2_i}) - \delta_2, \end{array} \\ \frac{F_{c_2}(\tau_2) - F_{c_2}(\tau_2 - \delta_2)}{F_{c_2}(\tau_2 + \delta_2) - F_{c_2}(\tau_2 - \delta_2)} & \text{if} \quad \begin{array}{l} r_i < \tau_1(w_i, c_{1_i}) - \delta_1 \quad \text{and} \\ |r_i - \tau_2(c_{2_i})| \leq \delta_2, \end{array} \\ \begin{array}{c} \frac{F_{w,c_1}(\tau_1) - F_{w,c_1}(\tau_1 - \delta_1)}{F_{w,c_1}(\tau_1 + \delta_1) - F_{w,c_1}(\tau_1 - \delta_1)} \times \\ \frac{F_{c_2}(\tau_2) - F_{c_2}(\tau_2 - \delta_2)}{F_{c_2}(\tau_2 + \delta_2) - F_{c_2}(\tau_2 - \delta_2)} \end{array} & \text{if} \quad \begin{array}{l} |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \quad \text{and} \\ |r_i - \tau_2(c_{2_i})| \leq \delta_2, \end{array} \\ 1 & \text{if} \quad \begin{array}{l} r_i < \tau_1(w_i, c_{1_i}) - \delta_1 \quad \text{and} \\ r_i < \tau_2(c_{2_i}) - \delta_2. \end{array} \end{cases} \tag{C.11}$$

We can then characterize the local propensity score by calculating the limit of C.11 when $(\delta_1, \delta_2) \to (0, 0)$ and we have that:

$$\lim_{(\delta_1,\delta_2)\to(0,0)} \tilde{\pi}_{p,i} = \begin{cases} 0 & \text{if} \quad r_i > \tau_1(w_i, c_{1_i}) + \delta_1 \text{ or } r_i > \tau_2(c_{2_i}) + \delta_2, \\ 0.5 & \text{if} \quad |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \text{ and } r_i < \tau_2(c_{2_i}) - \delta_2, \\ 0.5 & \text{if} \quad r_i < \tau_1(w_i, c_{1_i}) - \delta_1 \text{ and } |r_i - \tau_2(c_{2_i})| \leq \delta_2, \\ 0.25 & \text{if} \quad |r_i - \tau_1(w_i, c_{1_i})| \leq \delta_1 \text{ and } |r_i - \tau_2(c_{2_i})| \leq \delta_2, \\ 1 & \text{if} \quad r_i < \tau_1(w_i, c_{1_i}) - \delta_1 \text{ and } r_i < \tau_2(c_{2_i}) - \delta_2. \end{cases} \tag{C.12}$$

Figure C.1: Characterization of the Local Propensity Score Conditional on a COAR Offer



Notes: This figure plots 1st-choice, 2nd-choice, and pending offers (conditional on receiving a general COAR offer) as determined by the cutoffs in the second step of the COAR assignment mechanism. The blue, red, and green areas correspond to those that receive a 1st-choice, a 2nd-choice, and a pending offer, respectively. The figure also indicates the conditional propensity score of each type of offer ($\tilde{\pi}_{i,c_1}$, $\tilde{\pi}_{i,c_2}$, $\tilde{\pi}_{i,p}$) as determined by each cutoff (τ_1, τ_2) and the respective bandwidth (δ_1, δ_2). Both bandwidths' upper and lower limits determine nine regions, each having its own vector of the three propensity scores.