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

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Abstract

In contexts without standardized tests, college admissions could reward high school reputation over effectiveness, a phenomenon we explore 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 gains in learning, graduating from exam schools improves college applications, admissions, and enrollment, especially at top private universities. These findings are partly attributable to exam schools signaling students' abilities. Estimates of the effects of marginally obtaining the IB diploma on college outcomes are consistent with the signaling mechanism. We next estimate and validate as causal value-added models on college outcomes for all schools in Peru. Compatible with the exam school effects, value-added on learning does not predict school effects on college outcomes after controlling for average graduates' characteristics. Our findings underscore how information frictions can perpetuate inequality when standardized tests are unavailable.

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1 Introduction

The debate surrounding the role of standardized tests for college admissions remains a contentious issue (Harper, 2023; Zwick, 2023). Advocates argue that these tests are meritocratic and give colleges a comparable metric across applicants from diverse backgrounds benefiting talented low-income students (Chetty et al., 2023). Critics contend that standardized tests can perpetuate inequalities, as they may not accurately reflect a student's potential and are influenced by socioeconomic and race factors, test preparation, and bias (Jacob and Rothstein, 2016). Standardized tests may also not predict college performance better than other available information, such as high school grades (Rothstein, 2004). While there has been progress in understanding the impact of eliminating standardized tests from college admission decisions, for instance, by changing students' high school academic investments (Borghesan, 2023), the aggregate consequences of removing standardized tests remain an ongoing inquiry.

A potential consequence of eliminating standardized tests from college admissions could be a higher reliance on alternative sources of information, including the reputation of the graduating high school. While evidence from the US shows compatible effects between school value-added on test scores and longer-term outcomes, including college enrollment (Dynarski et al., 2013; Angrist et al., 2016, 2023), when standardized tests are unavailable, college admissions authorities cannot observe specific human capital gains that reward effective schools at improving learning. As a result, without the information conveyed in test scores, college admissions could favor high schools' reputation over effectiveness by using the graduating school as a signal of applicants' ability. This shift from effectiveness toward reputation could reinforce existing inequalities as students from less advantaged backgrounds have fewer opportunities to graduate from prestigious schools. The absence of standardized tests can also generate further information frictions in education markets, as schools' effectiveness or ineffectiveness in enhancing learning may not necessarily translate into longer-term outcomes.

In this paper, we study school effects on college outcomes in Peru and relate these effects to their reputation—measured by the average characteristics of their graduates—and their effectiveness on learning. Peru presents a unique context to explore this question due to the absence of a standardized secondary 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 there are nationwide standardized tests in the country, these are usually low-stakes, taken three and eight years before high school graduation, and have no impact on college admissions decisions. Yet, these tests allow to explore the connection between school reputation and effectiveness to schools' effects on college outcomes.

To explore this connection, we leverage a comprehensive dataset with information on students' applications, admissions, and enrollment at almost all universities in Peru. The data has the advantage of distinguishing between the different 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 exist in Peru: (i) an exam admission mode, where applicants take a university-specific admission test; (ii) an extraordinary admission mode, which provides benefits for applicants who satisfy specific conditions established by each university and, in many cases, exempts them from the regular admission exams; and (iii) preparatory academies, where participants take preparatory courses offered by the university and top students receive direct admission.

Descriptive evidence shows that students from more advantageous socioeconomic backgrounds benefit the most from extraordinary admissions. Top private universities also admit a higher proportion of applicants via this admission mode than public universities. While around 50% of students graduating from secondary schools in the 99th percentile of the income distribution are admitted via extraordinary admissions at private institutions, such proportion is less than 5% for students graduating from secondary schools in the bottom half of the income distribution.

Motivated by this evidence, we estimate school effects on college outcomes and distinguish the mode of admission. First, we assess the causal impact of selective public exam schools, the *Colegios de Alto Rendimiento* (COAR) Network, on college outcomes. The COAR Network is a set of 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. COAR follows 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 in the top 10 of their class, using a series of tests for admissions, and allowing enrollees to interact with other high-achieving peers. COAR schools also have more resources from the government and a different teacher hiring system than traditional public schools.

To identify causal effects of the COAR Network, we use the government's assignment mechanism in a fuzzy regression discontinuity designs (RDD). As other school assignment mechanisms previously implemented (Abdulkadiroğlu and Sönmez, 2003; Pathak and Sönmez, 2008), the COAR mechanism lacks some desirable theoretical problems. However, as the now commonly used deferred-acceptance (DA) algorithm, the COAR mechanism uses applicants' types, the combination of 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 that determines who gets an offer from any COAR school, and 1st- and 2nd-choice cutoffs that determine the specific COAR school from which the applicant receives an offer.

The variation in offers around these cutoffs lays the ground for an RDD. Such research design needs to account for two sources of selection bias. On the one hand, as in a typical RDD, running variable controls and comparing applicants inside a bandwidth around admission cutoffs account for admission scores not being random. On the other hand, a full non-parametric conditioning of the applicant's type solves the selection bias from the assignment due to applicants' preferences and priorities. In practice, however, as only a few observations share the same type, Abdulkadiroğlu et al. (2017a) propose to condition on the propensity score of each school offer rather than full non-parametric conditioning. 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 arising from the COAR mechanism.

We leverage the assignment mechanism in a single-instrument and multiple-instruments fuzzy RDD. Our first strategy is a typical fuzzy RDD, where whether the applicant clears 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 the applicant's type by conditioning on this variable with running variable controls that also vary by region. Our second strategy leverages all the variation in first-round offers from the assignment mechanism by using the school-specific offers, determined by the three cutoffs, as instruments for COAR graduation. Rather than full conditioning on applicants' type, we account for selection by conditioning on the vector of school-specific propensity scores.

Our results show that graduating from the COAR Network improves college outcomes, mainly at top private universities, with extraordinary admissions explaining between 40% to 60% of such effects. Marginally admitted COAR graduates are 11.9 percentage points (p.p.) (standard error (s.e.) 5.4 p.p.) more likely to attend college, with very similar estimates from the multiple-offers model. Top private institutions drive these effects, with an estimate of 15.8 p.p. (s.e. 3.8 p.p.) on top-10 private enrollment in the single-offers model and of 9.4 p.p. (s.e. 2.2 p.p.) in the multiple-offers model. As for the admission mode, the estimates from the multiple offers model show 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 via extraordinary admissions at private universities, with these effects mainly coming from institutions in the top 10.

We next explore the mechanisms driving these effects and provide supporting evidence of universities using the graduating secondary school as a signal of applicants' abilities. First, despite COAR schools differing from traditional public schools in various aspects, including peer quality, the evidence of COAR's effect on human capital is, at best, inconclusive. A previous evaluation of COAR using an analogous strategy to our single-offer RDD finds no impact on test scores and non-cognitive skills (Hatrick and Paniagua, 2021). Moreover, after accounting for differential selection in universities' admission exams, our estimates show no effects of COAR graduation on admissions tests performance. Our estimates are similar in magnitude and precision to previous studies finding little evidence of elite schools on learning.

We also present additional empirical exercises that directly support the signaling story. As the effects on admissions can be driven by students' behavior, for instance, by COAR encouraging students to apply more to college, we test for signaling by only focusing on universities' admission policies. In particular, we estimate COAR effects on the eligibility to apply via extraordinary admissions at different institutions. The analysis considers two types of extraordinary admissions: whether the graduating school is on the list of eligible schools for special admissions, and, as COAR schools offer the International Baccalaureate Program (IB), whether the university has special admissions for IB students.

Our estimates reveal substantial COAR graduation effects on the number of institutions that allow applicants to apply via extraordinary admissions. COAR graduates are eligible to apply to about 28 more universities (s.e. 0.106) and 4.2 (s.e. 0.062) top-10 universities via extraordinary admissions, with around 30% to 50% being private institutions, respectively.[1] Likewise, after accounting for whether marginally admitted COAR graduates received the IB diploma, COAR graduates are eligible to apply to 5.24 more private (s.e. 0.788) and 1.13 more public universities

[1] Interestingly, while more public universities also have special admissions for COAR graduates, the number of available slots is only one or two, explaining the overall larger effects at private institutions.

(s.e. 0.170) via IB admissions.

In our final exercise for the signaling mechanism, we show that top private universities use the IB diploma as a signal for applicants' skills among COAR graduates. We leverage that students must score at least 24 points in IB subjects to receive the diploma and compare COAR students who marginally earn the IB by one point versus those who didn't. We perform the comparison within schools and find balance in an array of academic and non-cognitive skills, implying that the only distinction between the two groups is the IB. Our results are consistent with the IB signaling applicants' skills; earning the diploma increases by 10.7 p.p. (s.e. 3.8 p.p.) extraordinary admissions and by 17.3 p.p. (s.e. 4.7 p.p.) enrollment at top-10 private universities. Although we cannot entirely dismiss other factors like shifts in aspirations or COAR providing better information about college programs, these additional empirical exercises offer supporting evidence of the signaling mechanism.

We next explore the connection between school effects on college outcomes, school reputation, and effectiveness on learning for other secondary schools in Peru. We estimate school value-added models on college outcomes by controlling in a flexible way for achievement levels in math and reading, socioeconomic conditions, and parental and household characteristics three years before high school graduation. The comparison between the value-added estimates and the quasi-experimental variation from the multiple-offers COAR model provides the basis of an empirical test to assess the causality of the school value-added measures (Angrist et al., 2017), with such a test finding little evidence of bias in our high school value-added estimates on college enrollment and admissions at private universities. We also present additional validation tests uncovering little influence of unobservable factors in biasing our school value-added estimates.

After validating the value-added estimates, we relate such effects to school reputation, measured by the average test scores and socioeconomic background of its graduates, and value-added on learning, measured by value-added to test scores between 2nd grade in primary and 2nd grade in secondary school. Our results show that after controlling for average scores and socioeconomic background, school effectiveness on learning doesn't predict effects on college outcomes, especially at private universities. Moreover, the variable explaining most of the variation in secondary school effects on college outcomes is the average socioeconomic background of a school, which is also the main predictor of eligibility for extraordinary admissions at top private universities.

Motivated by the importance of the school's average socioeconomic background for eligibility for extraordinary admissions, we compare such eligible schools with three other groups: (1) similar schools in value-added to test scores, (2) similar schools in average scores of graduates, and (3) COAR schools. These comparisons show that despite some schools having similar value-added on learning or average scores, the school value-added to college outcomes between eligible schools and these groups differ significantly, especially at top private universities, and mainly through extraordinary admissions. By contrast, differences in school value-added on college outcomes, including extraordinary admissions at top private universities, between eligible and COAR schools are either small or tend to favor the COAR Network. This contrast suggests that despite the little evidence of COAR schools generating human capital gains, they provide low-income talented students with a signal in the college market that reduces income gaps in college quality and segregation in the college market.

Our results contribute to four branches of the literature. First, the study contributes to the literature on the effects of elite schools. Our findings show that even without notable gains in human capital, public elite schools can improve college outcomes. While there is some evidence that access to higher-achieving schools can improve students' outcomes (Pop-Eleches and Urquiola, 2013), most of the findings of elite public schools show no gains in achievement 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). Furthermore, even when there are gains in test scores, elite public schools can negatively impact other outcomes such as the dropout rate (Dustan et al., 2017) and self-confidence (Fabregas, 2017). Our findings contribute to this literature by showing that, in the absence of comparable measures of skills, elite public schools improve longer-term outcomes by allowing talented students to signal their abilities.

The study also contributes to the literature on school effects across different outcomes. While evidence in other contexts shows that school effects on short-term outcomes, such as test scores, predict school effects in longer-term outcomes (Angrist et al., 2016), our findings suggest that in context without standardized testing, that link is less clear. More recent studies explore whether parents' preferences for schools depend on school reputation or school effectiveness (Abdulkadiroğlu et al., 2020; Beuermann et al., 2022), with our findings suggesting similar frictions affecting universities' perceptions of school quality.

Third, our results contribute to the evidence on policies affecting equity in higher education access. While most of this evidence has focused on financial aid and support for college enrollment and completion (Angrist et al., 2021; Bucarey et al., 2020; Solis, 2017; Londoño-Velez et al., 2023) for low-income students, our results suggest that providing opportunities to signal their talent might also improve their college outcomes. Our results in Peru also align with recent evidence from the US, showing that high-income students disproportionately benefit from non-academic special admissions, with such non-academic credentials being stronger for applicants from private high schools with affluent student bodies (Chetty et al., 2023).

Finally, our results relate to the distinction in the value of education between signaling and human capital (Spence, 1973). While most of the empirical evidence around signaling has focused on the effects of alternative high school degrees (Jepsen et al., 2016) or college reforms (Arteaga, 2018) and effects in the labor market (MacLeod and Urquiola, 2015; MacLeod et al., 2017; Sekhri, 2020), our findings suggest that such considerations are also present in college admissions. Specifically, in settings where admission authorities have little information on the potential quality of students, admission authorities may rely on available signals such as the graduating school or prestigious degrees like the IB diploma, generating 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 available data. Section 4 documents the impact of COAR schools on college outcomes and explores the main mechanisms explaining these effects. 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. This range caters to various preferences and budget constraints, with 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 and previous evidence leveraging admission lotteries shows some encouraging evidence of charter effects on learning (Lavado et al., 2019).

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 processes.

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 widely 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 the quality of higher education, including creating an entity to monitor universities and publishing rankings, which we use to classify institutional quality.

As described before, a distinctive feature of Peru's higher education system is the absence of a standardized high school exit exam. As a result, the university admission process is decentralized and lacks a uniform metric for assessing student abilities nationwide. Without such a metric, universities must either gather their own assessments of student abilities or rely on the available information. Traditionally, this has led universities to conduct their own admission exams, implying students need to sit for multiple tests when applying to several institutions. Most universities employ a cutoff system for these exams, admitting students based on the number of available slots in their programs.

Many private universities have introduced an alternative admission method known as extraordinary admissions. This type of admission provides benefits to applicants who meet specific criteria determined by each university. In many cases, applicants can entirely waive an 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 than regular admission exams.

The criteria for extraordinary admissions vary among institutions, often including the identity and reputation of the applicant's high 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.[3] Additionally, many universities favor applicants from high schools offering the IB program, providing immediate admission to applicants who have earned 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

[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.

[3] Appendix Figure A.1 presents a specific example of the list of high schools that can apply via extraordinary admissions to Universidad del Pacífico in 2021-22.

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

This section describes our data sources and the use of various administrative records to explore high school effects on college outcomes.

3.1 Data Sets

We combine various administrative records 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 high 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.

In addition, 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 high 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 two cohorts of COAR applicants (2016 and 2017), these standardized tests allows us to have a nationwide comparable measure of academic ability to test for balance. Second, these datasets enables us to conduct a general analysis of high school effects in Section 5. Specifically, to estimate high school value-added models on learning by matching primary to high school test scores for the same students; and, to later estimate high school value-added models on college outcomes.

4. College applications and enrollment files: Our two final data sets are higher education 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 type. Distinguishing between applicants admitted via exams and alternative methods is critical to explore mechanisms driving high school effects on college outcomes. The enrollment files have information on the final enrollment decisions of applicants.

We use application and enrollment files to construct college outcomes that measure students' application decisions, college admissions, and enrollment. We distinguish between various types of universities by examining separately outcomes for public and private institutions. We also use the government ranking to classify the top 10 universities as a measure of institutional quality. Finally, for application and admission outcomes, we also discriminate between exam and other types of admissions. Data Appendix B provides more details of the match between the application, admissions, and enrollment files.

Sample of analysis: For the COAR Network effects in Section 4, our universe of analysis, the *COAR Sample*, are all COAR applicants between 2015 and 2017. Our second sample is the *All High Schools Sample*, which we use to estimate other high school effects in Section 5 and corresponds to students in 2nd grade in high school in 2015 and 2016, for whom the census-wide standardized test is available. These two samples overlap for the 2016-17 COAR applicant cohorts. For the 2015 COAR cohort, however, there is no national standardized test, as the government implemented it for the first time in 2015 when they were already in 3rd grade. Estimates of COAR effects are similar when we exclude this cohort, but we lose some statistical power due to a smaller sample size.

3.2 Descriptive Evidence

This section presents some descriptive evidence of universities' admission policies and how they relate to average high school characteristics.

First, we explore whether admission modes vary by universities' characteristics. Panel A of Table 1 reports the proportion of each admission mode over total admissions and classifies universities into public or private and by their institutional rankings. There is wide heterogeneity in admission policies between public and private universities, especially among the top-20 institutions. While the average rate via admission exams is around 67% and 77% for top-10 and top-20 public universities, such a rate is only 37% and 39% for top-10 and top-20 private universities, respectively. More striking, around 55% of admitted students in the top-20 private institutions are extraordinary admissions, which contrasts a rate of less than 10% for public institutions. On the other hand, public universities have more preparatory admissions than private institutions. The admission mode rates between public and private for lower-ranked universities (either in the top 32 or unranked) are similar.

The consequences of such admission policies and the type of university students attend can potentially shape longer-term impacts on labor market outcomes. While estimating university effects on employment and wages is out of the scope of this paper, Appendix Figure A.2 reports average first-job wages by whether the university is public or private and its ranking. Overall, private universities in the top 20, the ones mainly using extraordinary admissions, have higher average wages than public universities with similar rankings and than lower-ranked private and public universities.

Next, we explore how different admission modes relate to average high school characteristics. We combine the 2015-16 standardized tests files, which include test scores and socioeconomic information for all students three years before high school graduation, with university applications and admissions. We can then characterize the average socioeconomic index of the graduating high school and the proportion of students admitted to each university by each specific admission mode.

Figure 1 reports average admission rates at private (Panel A) and public (Panel B) universities for all high school graduates at each percentile (100 groups) of average high school socioeconomic index. Schools with a higher average socioeconomic index, graduate more students from advantageous socioeconomic backgrounds. The figure reports unconditional admission rates that do not account for students' application decisions. Appendix Figure A.3 depicts the correlation between the percentile of the index and high classification as either public or private, revealing that while the bottom of the distribution is dominated by public high schools, the top is mainly composed by private high schools.

The evidence in Figure 1 reveals persistent income segregation from high school to college. Most students graduating from high schools at the bottom of the average socioeconomic index distribution, who are graduating from public high schools, are not admitted to any university. By contrast, students graduating from high 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% and, mainly, through the admission exams, with preparatory academies being the second most common admission mode. While there is some gradient between the high school percentile and these admission rates, the curve is relatively flat.

By contrast, the evidence in Panel A shows a striking relationship between admission rates at private institutions and the high school percentile. The difference in the gradient between exam and extraordinary admissions is even more remarkable. While the first one is pretty linear, the second one is convex, showing that high school graduates at the top of the distribution benefit disproportionately from this type of admissions. The admission rate for the 100th percentile, for example, shows that more than half of the students graduating from these high schools are admitted via extraordinary admissions at a private university. For the 99th percentile, the admission rate is still high but lowers to around 40%, while at the 90th percentile the admission rate is around 20%. In summary, the evidence suggests that extraordinary admissions are mainly used by top private institutions and benefit students graduating from high schools at the top of the average socioeconomic distribution.

Finally, as the first part of our empirical analysis focuses on estimating COAR effects on college outcomes, Figure 1 reports average admission rates for COAR schools in triangles. COAR schools serve mainly middle-income students with the average socioeconomic index ranging between the 53rd and the 74th percentile. More notable is that the admission rates at both private and public universities, either by exam or extraordinary admissions, are relatively high. For instance, some COAR schools' average extraordinary admission rates are comparable to those of other secondary schools above the 90th percentile of the average socioeconomic index. Likewise, extraordinary admissions rates at public universities are higher than for other schools in the distribution.

This descriptive evidence shows that COAR schools have similar or better average admission rates than secondary schools at the top of the income distribution. However, such evidence cannot be interpreted as causal. The following section explores the causal effects of the COAR Network on college outcomes.

4 COAR Network Effects

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

4.1 Assignment Mechanism

We first describe the COAR assignment mechanism, designed by the government, and explain how it serves our empirical design. Similar to other school assignment mechanisms (Abdulkadiroğlu and Sönmez, 2003; Pathak and Sönmez, 2008), the COAR mechanism harbors significant flaws, including not being strategy-proof and imposing restrictions on students' preferences. Despite these shortcomings, our main interest lies in the variation generated by the mechanism in school offers to estimate COAR causal effects rather than in its desirable 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.[4] 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 $\tilde{\mu} : \mathcal{I} \rightarrow \mathcal{S}$, 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

[4] For the COAR assignment, 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.

must remain in a traditional public school.[5] The COAR mechanism, denoted by μ, considers three main variables for the assignment: applicants' priorities and preferences, which determine an applicant's type, and the admission score.

The only variable determining schools' priorities for students is the applicants' region of origin. Let $l_i \in \mathcal{L}$ denote the region of origin of the applicant, with $l_i = 1, \cdots, S$ indicating applying from regions with a COAR school and $l_i > S$ indicating applying from a region without a COAR school. The region of origin is essential, as the government assigns each region a quota for overall COAR slots across the whole network. Likewise, for the assignment of 1st-choice offers, school s also prioritizes applicants from the same region as their location ($l_i = s$), and applicants from regions without a COAR school ($l_i > S$) are pooled together and considered as a separate group. For this reason, let w_i denote a binary variable indicating whether the applicant's region has a COAR school: $w_i = 1$ if $l_i \leq S$ and 0, otherwise.

The second determinant of applicants' type is the vector of preferences. For the COAR mechanism, applicants submit preferences by ranking exactly two COAR schools, with c_{1_i} and c_{2_i} denoting the first and the second choice of applicant i, respectively. Unlike other allocation mechanisms, the government imposes specific constraints on applicants' preferences. For applicants from regions with a COAR school, $l_i \leq S$, their first choice must also be the school within their home region, $c_{1_i} = l_i$, and they can freely choose their second choice. By contrast, applicants from regions without a COAR school ($l_i > S$) can rank their two top choices without restrictions.

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

As for the DA with non-lottery tie-breakers (Abdulkadiroğlu et al., 2022), the COAR mechanism matches applicants to COAR seats as a function of applicants 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 corresponds to the composite score in the COAR admission tests. The COAR assignment mechanism uses these three inputs to assign first-round offers, with the process divided into two phases: the assignment of any COAR offer and the assignment of school-specific offers.

We provide all the details of the algorithm in Appendix C, but here, we briefly describe its steps to assign 1st-round offers, which is the quasi-random variation we leverage 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 with the region-specific quota determining a general admission cutoff denoted by $\tau_0(l_i)$, with applicants clearing this cutoff receiving an offer to join any COAR school. Note that this quota is defined for all regions regardless of whether they have a COAR school.

In the second step, the algorithm assigns school-specific offers. First, it allocates 1st-choice offers to applicants from regions with a COAR school by determining a same-region quota for all schools. Then, the algorithm assigns 1st-choice offers for applicants from regions without a

[5] The number of slots available for a pending offer is the difference between the total COAR slots and those assigned to specific COAR schools $q_p = Q - |\{i \in \mathcal{I} : \ 0 < \tilde{\mu}(i) \leq S\}|$

COAR school by ranking them within their first choice. This process derives into a 1st-choice cutoff for each applicant $\tau_1(w_i, c_{1_i})$ that is a function of 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 rejected applicants by their first choice within their second choice. If the second choice is oversubscribed, the algorithm defines a cutoff $\tau_2(c_{2_i})$, with applicants clearing this cutoff receiving an offer from their second choice and rejected applicants receiving 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 lies in using the variation in equation 1 to estimate the causal effects of G_i, a variable indicating whether applicant i graduates from a COAR school, on Y_i, applicant's i college outcome. While the COAR assignment mechanism doesn't randomly allocate G_i, equation 1 provides quasi-experimental variation in 1st-round offers that allow for an instrumental variable (IV) strategy to estimate COAR graduation effects.

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

The single-instrument model provides variation as in a typical RDD, allowing us, for example, to present the main results graphically. The multiple-instruments model, on the other hand, provides three benefits. First, a multiple-instruments model improves the estimates' precision compared to a single-instrument fuzzy RDD. Second, the multiple-offers framework allows testing whether effects are homogeneous or heterogeneous across schools in the COAR Network. In particular, rejecting the over-identification restrictions test implies that school-specific treatment effects are heterogeneous as different combinations of the school-specific offers as instruments derive into different 2SLS COAR graduation estimates. Moreover, the multiple-offers model allows us to adapt the empirical test in Angrist et al. (2017) to test for bias in school value-added models on college outcomes for all secondary schools in Peru. We perform such a validation exercise in Section 5.2.

The IV models that leverage the assignment of 1st-round offers as instruments must account for two potential sources of selection bias. First, offers depend on r_i, the admission score, a non-lottery tie-breaker that is not randomly assigned. Following the standard practices of RDDs, limiting the sample to observations inside a bandwidth δ around the admission cutoffs and flexibly controlling for the running variable can eliminate this first source of selection bias.

The second source of bias 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 instance, the single-instrument 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, for a design that leverages all the variation in the assignment mechanism, as in the multiple-instruments model, full non-parametric conditioning on applicants' type implies conditioning on the combination of region, l_i, and applicants' preferences c_{1_i}, and c_{2_i}. While such conditioning eliminates this source of bias, it is unattractive when only a few observations share the same type, as the sample size within each type cell would be small. As proposed by Abdulkadiroğlu et al. (2017a), a solution for such a problem is to condition on the propensity score of receiving a school offer for each type rather than on full type non-parametric conditioning as in other stratified randomized research designs (Rosenbaum and Rubin, 1983).

For our design, we follow Abdulkadiroğlu et al. (2017b) and Abdulkadiroğlu et al. (2022), who characterize a local propensity score in the Serial Dictatorship (SD) and Deferred Acceptance (DA) school assignment mechanisms with non-lottery tie-breakers, and extend such 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 or a school-specific propensity score. As for these mechanisms, conditioning on the propensity score of the COAR mechanism eliminates the selection bias arising 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 of them. While we characterize the vector of propensity scores in detail in Appendix C.2, here we briefly explain this characterization.

First, 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 propensity score of a COAR offer, which we denote by π_i:

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

with $\tilde{\pi}_{s,i} = \mathbb{E}\left[D_{s,i} = 1 | \theta_i = \theta, D_i = 1\right]$. As shown by Abdulkadiroğlu et al. (2022), the local propensity score π_i takes three values when $\delta_0 \rightarrow 0$: 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 $\delta_1 \rightarrow 0$ and $\delta_2 \rightarrow 0$. 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 when the bandwidths shrink to 0. As 1st-choice offers are processed first, applicants inside the τ_1-bandwidth have a conditional propensity score $\tilde{\pi}_{c_{1_i},i}$ of 0.5 of receiving an offer from their first choice. The remaining local propensity score to add up to 1 (since we condition on $D_i = 1$) depends on where their score lies in comparison to τ_2. If the score is above the τ_2-bandwidth ($r_i > \tau_2 + \delta_2$), then $\tilde{\pi}_{c_{2_i},i} = 0.5$; when the applicant doesn't receive an offer from their 1st choice, which is as good as random within the τ_1-bandwidth, they receive an offer from their second choice. By contrast, if they lie below the τ_2-bandwidth ($r_i < \tau_2 - \delta_2$), then their counterfactual option is a pending offer, with $\tilde{\pi}_{p,i} = 0.5$. If they lie within the τ_1- 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-instrument 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:

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

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-instruments model: Our second empirical strategy leverages all the variation from the assignment mechanism by using a multiple-instruments strategy, where the set of school-specific offers is used as instruments for COAR graduation. This school-specific offers model is also our primary tool to validate other school effects on college outcomes in Section 5. The following set of equations describes this 2SLS 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. As described in Section 4.1, an applicant would receive a pending offer when they clear the general regional admission cutoff, but do not receive an offer from their 1st- and 2nd-choice schools. 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, as described in Section 4.2, 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

Our empirical analysis starts by estimating the first stage of the single- and multiple-instruments model on COAR graduation. For several reasons, the 1st-round offers are not a perfect predictor of COAR graduation. For instance, just for enrollment decisions, applicants may prefer to enroll in a traditional public school than in the COAR school from which they receive an offer. 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 based on the government application 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-instruments 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. The effects of the remaining two COAR schools are 27 and 43 percentage points.

We next explore how this increase in COAR graduation relates to changes in the average characteristics of the applicants' school graduates.[6] Columns 4 to 6 in Table 2 report the 2SLS estimates of COAR graduation on average school graduates characteristics for the single-instrument model, with Panels D to F in Figure 2 showing the analogous RD plots.

On average, applicants marginally admitted to the COAR Network experience a sharp difference in average graduates characteristics. The 2SLS estimates in the single-instrument 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. Overall, graduating from the COAR Network affects the average characteristics of graduating peers, as it has been documented for elite public schools in other contexts (Abdulkadiroğlu et al., 2014; Dobbie and Fryer, 2014; Lucas and Mbiti, 2014).

[6] 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.

4.4.2 2SLS Effects on College Outcomes

Next, we explore COAR graduation effects on college outcomes. Table 3 reports estimates of the second stage of the single-instrument (equation 3a) and multiple-instruments (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-instruments models, respectively.

Graduating from the COAR Network has a statistically significant effect on any college enrollment. The single-instrument 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.). Compared to the control mean, this represents an increase of 17% in college enrollment. The over-identified estimates using the multiple-instruments model are relatively similar to those from the single-instrument model, showing an effect of COAR graduation on college enrollment of 9.1 p.p. (s.e. 3.0 p.p.). The over-identification test does not reject the null hypothesis of homogeneous effects of school-specific COAR offers on college enrollment.

Enrollment at private universities is the primary driver of the positive impact on college enrollment. While the estimates of the single-instrument model for private university enrollment show a statistically significant effect of 19.6 p.p. (s.e. 6.1. p.p.), the results show a non-significant effect of -4.6 p.p. (s.e. 5.9 p.p.) on public university enrollment. The 2SLS estimates in the multiple-instruments model are also similar. COAR graduation positively affects private university enrollment by 17.4 p.p. (s.e. 3.5. p.p.), whereas the effect on public enrollment is a significant effect of -7.9 p.p. (s.e. 3.5 p.p.).

The estimates also show larger effects for top private than for top public universities. The 2SLS estimates in the single-instrument model show a positive and significant effect of 15.8 p.p. (s.e. 3.8 p.p.) on enrollment at top private universities. Compared to the control mean, this represents an increase of approximately 154%. By contrast, COAR graduation has a non-significant effect on enrollment at top public universities of only 0.1 p.p. (s.e. 3.3 p.p.). The 2SLS estimates from the multiple-instrument model follow the same pattern with smaller effects. The impact on enrollment at top private universities is 9.4 p.p. (s.e. 2.2 p.p.), contrasting a not statistically significant effect of -1.7 p.p. (s.e. 1.9 p.p.) at top public universities. The over-identification test marginally rejects the null hypothesis of homogeneous effects for the latter outcome, suggesting that COAR schools have heterogeneous impacts on enrollment at top public universities.

Table 4 explores whether effects on applications and admissions explain the effects on enrollment. Columns 1-2 report the 2SLS estimates for applications and admissions at private universities, and columns 4-5 for the same outcomes at public universities. Columns 3 and 6 replicate the private and public university enrollment 2SLS estimates in Table 3 for comparison. Section I reports results for all universities, and Section II for top-10 universities. Within each section, Panels A and B show the 2SLS estimates in the single- and multiple-instruments models, respectively.

The single- and multiple-instruments models yield the same conclusions about the effects of COAR graduation on application and admission to all private and public universities. The results on application show that COAR graduation increases the likelihood of applying to private universities between 27.7 p.p. to 35.7 p.p. (s.e. 3.6-6.5 p.p.) and has no impact on applications to public universities. The effects on admissions are consistent with those on applications. COAR graduates have an admission rate to private institutions between 19.7 p.p. to 22.4 p.p. (s.e. 3.4-6.0 p.p.) higher than marginally rejected COAR applicants, with such effects resulting in higher college enrollment.

The results in Section II of Table 4 show a similar conclusion for top-10 universities. COAR graduates apply at a higher rate, are more likely to be admitted, and enrolled more at top-10 private institutions, with smaller or no effects on the same outcomes for top-10 public institutions. The multiple-offers model rejects the over-identification test for top-10 applications and admissions for both public and private universities, suggesting some COAR schools are more effective than others at improving these outcomes. Notably, while COAR graduates apply more to top-10 public universities (Section II, column 4) by around 10.6 to 14.2 more p.p. (s.e. 3.0-5.6 p.p.), such higher application rates do not result in higher admissions (Section II, column 5) or enrollment (Section II, column 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 columns for admissions via preparatory academies.

The estimates show COAR effects on both exam (columns 1-2) and extraordinary (columns 3-4) applications and admissions at private universities, with no effects via preparatory academies (columns 5-6). For all private universities (Section I), effects on extraordinary admissions are larger than on exam admissions, while for the top 10, the effects are slightly smaller but similar in magnitude. Overall, this suggests that extraordinary admissions explain between 47% to 76% of the total effect on admissions.[7]

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

This section explores the mechanisms behind COAR's effects on college outcomes. We consider two potential mechanisms: human capital and signaling, finding more conclusive evidence about the latter. We also discuss other possible mechanisms we cannot completely rule out, such as

[7] Appendix Table A.2 reports analogous estimates for public institutions with non-significant effects on application and admission across the three admission modes for public universities. If anything, COAR graduation increases applications to the top-10 public universities, but, as discussed before, these effects on applications do not translate into higher admission rates.

changes in aspirations.

4.5.1 Human Capital Gains

One potential explanation for the effects on college outcomes is that COAR generates gains in students' academic and non-academic skills. However, consistent with the evidence for 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 suggest 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 examined COAR's effects on test scores and non-cognitive skills for the 2016 cohort, finding no evidence of learning gains (Hatrick and Paniagua, 2021). Appendix Table A.3 reports these estimates, with precise zero effects on math and reading scores. While the estimates on non-cognitive skills are less precise, they vary widely in direction and magnitude, from some positive effects on grit to negative impacts on school attitude and leadership, with none being statistically significant. Overall, the results from this evaluation don't support human capital gains as a relevant mechanism.

As a second exercise, we explore whether COAR affects performance in admission exams. A potential concern with such analysis is selection. If COAR graduation affects the institutions and admissions modes of college applications, there could be differential attrition in observing an exam score at each university. To address the selection concern, we estimate COAR effects on exam scores for universities with little evidence of differential attrition. Panel A of Appendix Figure A.5 reports the estimates of the effect of clearing the admission cutoff on the likelihood of observing an exam score for each of the 110 universities in the sample, and Panel B reports the p-values of the joint significance test of the set of offers for the multiple-offers model. We estimate COAR graduation effects on exam performance for a sample of universities, where we exclude those with statistically significant reduced-form effects on the likelihood of observing an exam score.

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

Overall, the results show little impact of COAR graduation on admissions exam performance. Regardless of the university sample restrictions, the single-offer model produces non-statistically significant estimates of 1st-round offers on exam scores between -0.003 and 0.011σ (s.e. 0.048-0.049), which translate into a COAR graduation effect between -0.006 and 0.023σ (s.e. 0.113-0.118). The multiple-offers model in Panel B reports even more precise 2SLS estimates with effects between 0.006 and 0.015 (s.e. 0.083). The estimates in the balanced attrition sample of both models are very similar to the ones for all universities in Appendix Table A.5. These effects and their precision are comparable to estimates of other studies finding negligible effects 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 show a negligible impact of COAR schools on learning. While it is impossible to completely rule out human capital gains, this additional empirical evidence suggests that learning gains are unlikely to be one of the main drivers of COAR graduation effects on college outcomes.

4.5.2 Signaling

The second mechanism we explore is signaling: whether COAR effects on college outcomes can be explained by universities relying on signals of students' abilities, including an applicant's graduating school. While some of the previous evidence is suggestive of this mechanism, such as the estimates on extraordinary admissions, aggregate effects on admissions combine students' application choices and universities' admissions policies. Hence, this section presents two additional empirical exercises to test for the signaling mechanism. For the first exercise, we estimate COAR effects on eligibility for extraordinary admissions, which only considers university admission policies and abstracts from students' application decisions. The second exercise estimates the effects of a second signal among COAR graduates: the effects of marginally obtaining the IB diploma.

The first exercise focuses on eligibility for extraordinary admissions. As discussed before, universities may infer higher skills from COAR students as the network has, on average, graduates with higher baseline achievement levels than counterfactual schools (columns 4-5 of Table 2). Moreover, COAR schools are recognized by the media and the public as elite public institutions targeting talented low-income students,[8] which can potentially influence universities' admission policies.

We use two methods to assess eligibility for extraordinary admissions. The first, an empirical approach, identifies a school as eligible if at least one graduate applies through a specific type of extraordinary admission. Our analysis focuses on admissions that favor certain schools, such as a list of preferred institutions or the IB diploma, and excludes other categories like class ranking or admissions for victims of violence. The second method evaluates eligibility for universities that appear in the government ranking, which only ranks the top 32 universities in the country. We examine each of these universities' admissions policies and classify a school as eligible for extraordinary admissions if it explicitly appears listed in the university admission documents[9]. For the case of IB admissions, we consider whether the school offers the IB and whether the university has a special admission mode for IB applicants.

[8]For example, El Comercio, a leading Peruvian media outlet, characterizes the COAR Network as "designed to offer high-quality education to the brightest students from 3rd, 4th, and 5th grades, who must clear a stringent examination to secure a spot" (El Comercio, 2014)

[9]Appendix Figure A.1 provides an example of such a list.

Table 7 reports the single- (Panels A) and multiple-offers (Panels B) model on the number of universities students are eligible for extraordinary admissions of preferred schools. Column 1 reports the results for all universities, and columns 4 and 7 for private and public universities, respectively, with Section I reporting the results for all universities and Section II for the top 10. Overall, the results show a large increase in the number of universities to which COAR graduates are eligible to apply compared to non-COAR graduates. Among all universities, the single-offer model shows an increase of 28.2 universities (s.e. 0.106), with 9.5 private and 18.7 public. Among these, 2.16 of the private universities and 2.00 of the public universities are in the top 10. The multiple-offer models reveal similar larger estimates, and the p-values of the over-identification tests suggest substantial heterogeneity among specific COAR schools on this eligibility. Appendix Table A.6 compares, for top-10 and top-32 universities, the empirical and the admission policies' documentation methods, finding very similar results.

Interestingly, while most of the effects on main outcomes on enrollment (Table 3) are on top private universities, the results on eligibility show larger increases for public institutions. The documentation we reviewed to construct the eligibility measures shows that most of these effects come from some public universities that designed special admission modes that only target COAR graduates but have limited slots.[10]

The International Baccalaureate Diploma

We also test COAR effects on extraordinary admissions eligibility via the IB diploma. The IB program is a two-year educational curriculum designed and managed by a nonprofit organization in Switzerland. Advocates argue that the IB provides an internationally accepted qualification for entry into colleges worldwide, as many universities recognize the program. Schools wishing to offer the IB program must undergo an authorization process and pay a fee, which stood at $12,233 USD in 2023. The Ministry of Education in Peru has managed all COAR schools to offer the IB program, which was mandatory for all COAR graduates up to 2017. Only COAR schools, schools for the children of the army, or elite private schools offer the IB program in Peru.

We find empirical evidence consistent with universities also using the IB diploma as a signal of applicants' ability. Columns 2, 5, and 8 of Table 7 report the estimates of COAR graduation effects on the number of all, private, and public universities, offering IB extraordinary admission. On average, COAR graduates are theoretically eligible to apply to approximately 21.35 additional universities (s.e. 0.109) due to the IB, with 17.35 private and about 4 public institutions. Among these universities, 7 rank in the top 10, including 5 private and 2 public universities.

As many COAR students do not end up receiving the IB diploma, columns 3, 6, and 9 account for whether a COAR graduate has actually obtained the IB. We restrict this analysis to students in the 2015-16 cohorts as we couldn't access the IB information for the 2017 cohort. The RD estimates show substantial effects even after accounting for receiving the IB. Such effects are

[10] For example, a university offered 278 slots for COAR graduates or graduates from any school who ranked in the top 2 of their class. Applicants took a simplified version of the admission exam, and slots were assigned in strict order of merit. Out of the 478 applicants, 44 were COAR graduates, with only 12 of them successfully securing an admission slot.

lower than in the earlier columns, suggesting that only about 30% of COAR graduates around admission cutoffs meet all requirements to receive the IB diploma. Yet, such numbers show substantial effects on extraordinary admissions eligibility via the IB, especially considering that marginal applicants are less likely to obtain the diploma than other COAR students.

To provide further evidence of the signaling mechanism, for our second additional empirical exercise, we estimate, among COAR graduates, the effect of marginally obtaining the IB diploma. We leverage that students must achieve a score of at least 24 points across six subjects to receive the diploma. The score in each subject depends on a sequence of external exams evaluated by an assigned external moderator. Our empirical design compares students who scored 23 points, marginally missing obtaining the diploma, with those who scored 24 points, who marginally qualify for it. Given the likely similarity in academic and non-academic abilities between these two groups, the only difference is the diploma itself.

Our strategy considers a fuzzy design as obtaining the diploma has additional requirements, such as completing the activities for the Creativity, Activity, and Service (CAS) component. The following system of equations describes the first and second stage 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} is the outcome of student i graduating from school s and cohort t. The variable IB_{irt} is a dummy variable equal to one when the student receives the IB diploma and zero otherwise. The variable Z_{ist} takes the value of one if a student achieves a total score of 24 in the IB program and zero if the score is only 23 points. All our estimations control for school-by-cohort fixed effects ψ_{st} as some schools may be better at the IB program training. We also present randomization inference p-values of the reduced form of this model following Cattaneo et al. (2020).

We first validate this empirical design by showing that obtaining a score of 24 vs. 23 points for the IB diploma doesn't correlate with academic or non-academic skills. Appendix Table A.4 reports the RF estimates of the system of equations 5a and 5b. The balance variables in this table include math and reading performance and different measures of self-reported psychological tests such as personality traits and stress. We also test whether there are any differences in social network measures, such as the number of friends, study partners, and centrality. The estimates show that the research design is valid as the two groups are similar across these dimensions. Our research design also exhibits a strong and large first stage, depicted in Figure 5. Our estimates indicate that achieving a score of 24 vs. 23 has a 74 p.p. increase (s.e. 2.9 p.p.) in the likelihood of obtaining the IB diploma.

Table 8 presents reduced-form and 2SLS estimates of the IB diploma on application, admission, and enrollment at top-10 universities, with Appendix Table A.7 showing the results for all universities. Overall, the IB signal affects admission and enrollment at the most selective private institutions. Section I reports the estimates for private universities, and Section II for public universities. Columns 1 and 2 present the results for applications and admissions via exams, columns 3 and 4 for extraordinary admissions, and columns 5 and 6 for preparatory academies, with column 7 reporting the estimates on enrollment.

The findings align with the IB signaling applicants' skills, with top private universities placing greater emphasis on such signals in their admissions processes than public universities. Column 7 shows that earning the IB diploma increases the probability of enrollment at a top-10 private university by 17.3 p.p. (s.e. 4.7 p.p.), an increase of roughly 138% relative to the control mean. Moreover, the estimate in column 4 indicates that extraordinary admissions primarily drive the positive effects on enrollment rates. Conversely, the impact of the IB diploma on enrollment or admission rates at public universities is not statistically distinguishable from zero, suggesting no effects for these universities.

Collectively, COAR graduates are more eligible to apply through extraordinary admissions and benefit from accessing additional signals of skills, such as the IB diploma. Both findings support signaling as a relevant mechanism to explain the observed COAR effects on college enrollment, which contrasts the, at best, inconclusive evidence for human capital differences.

4.5.3 Other Mechanisms: Aspirations and Information

We finalize this section by discussing two related mechanisms that could partially explain COAR effects on college outcomes: differences in students' aspirations and information about college opportunities. While evidence of these two mechanisms does not exclude signaling as a central factor explaining the main effects, we acknowledge that these are other potential channels we cannot entirely rule out.

We begin by examining the role of aspirations (Genicot and Ray, 2017). The issue of imperfect information in the higher education market is twofold: universities lack precise information on students' abilities, but students themselves are also not fully informed about their own skills. Both information frictions are exacerbated in contexts without standardized tests. In such a context, receiving an offer from a COAR school, advertised as targeting the most talented students in the media, has two signaling effects. First, it signals to the market of a student's abilities, and second, it signals to the student and their family of their potential.

Two pieces of evidence align with the aspirations mechanism. First, COAR graduation affects exam admissions at private institutions, with such effects likely resulting from students' application decisions. The observed increase in unconditional exam admissions (column 2, Table 5) is likely attributable to the higher application rates (column 1 of the same table). As the estimates in Table 6 reveal no significant differences in admission exam performance once selection biases are accounted for, higher aspirations could explain the effects on admissions by encouraging students to apply more to college.

Another related channel that we cannot completely rule out is differences in information about college opportunities (Hoxby and Turner, 2015; Dynarski et al., 2021). While aspirations could influence students' application decisions, COAR schools providing their graduates with better information about college opportunities could also explain some of the main effects. Even if the evidence about COAR schools' effectiveness at improving learning is inconclusive, COAR schools may have access to better sources of information about universities' admission policies and procedures. While the data doesn't allow us to differentiate between the aspirations and information mechanisms, the effects on exam admissions are likely driven by higher application rates, with the interplay of aspirations and better information being two central components influencing students' application decisions.

5 Other Secondary Schools

We next explore whether the results described in the previous section extend to other schools in Peru. In particular, whether school effects on learning outcomes or school reputation predict school effects on college outcomes. To this end, we estimate secondary schools' value-added (SVA) to learning and college outcomes. We first introduce a general value-added models framework and present the estimation and validation tests for college outcomes and learning. We also explore the connection 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 for value-added models, let $\mathcal{I}$ denote a population of students indexed by i, who enroll at or graduate from high school j. Let Y_{ij} denote the potential outcome for student i at school j. Under a constant-effects model[11], student i's potential outcome can be written as the sum of the mean potential outcome at school j, μ_j, and a composite measure of all other individual characteristics, such as family background, motivation, ability, and aspirations, captured by the term 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, $Y_{ij} - Y_{i0}$, corresponds to the value-added of school j for student i relative to a reference school. Under a constant-effects model, $Y_{ij} - Y_{i0}$, is the same for all students. Thus, plugging in equation 6 in 7, we have that:

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

where μ_0 is the average outcome for students in the reference school, β_j is the value-added of school j relative to the reference school, and a_i denotes 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 by using covariates to mitigate selection bias. In particular, we assume that the term a_i has the following functional form:

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

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

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. Plugging 9 into 8, we have that:

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

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

Our empirical models 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. As previous evidence shows that baseline scores are a critical variable to control for selection (Chetty et al., 2014a), our set of covariates also includes a cubic polynomial of math and reading scores in the primary school test and an analogous polynomial for the secondary school test for college outcomes. We also control for GPA, math, and reading grades from the previous year. Finally, we also control for whether the student is a COAR applicant with such effect varying flexibly by region. Appendix Table A.8 lists the set of covariates of the value-added models for each outcome.

We estimate SVA on college outcomes by estimating equation 10 on college enrollment and admissions by type of university and admission mode. The analysis sample includes all students who took the 2nd-grade high school standardized test in 2015 or 2016, characterized as the *All High Schools Sample* in Section 3. We define the relevant secondary school as the school a student is enrolled at three years after taking the secondary school test, which in most cases coincides with the graduating secondary school. We restrict the sample to schools that have at least ten students for each cohort to avoid imprecise estimates of the SVA.

We also estimate SVA on learning outcomes by estimating equation 10 on students' test scores in 2nd grade in secondary school. As our models flexibly control for students' test scores in 2nd-grade primary school, our main estimates rely on learning gains between these two periods. Most secondary schools in Peru offer the five years of this education level, with COAR schools being an exception as they only operate for the last three years. For this reason, while we cannot estimate SVA on test scores for COAR schools, we can estimate the learning gains of other high schools. We limit our sample to students who took the secondary school test in 2015 and 2016 so that the sample coincides with the cohorts for which we observe college outcomes, but our results are similar when the sample comprises all test-takers between 2015 and 2019. An implicit assumption of these models is that the SVA to learning in the first two grades of secondary school can be extrapolated to the last three grades.

As school-specific effects are estimated with errors and 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. In particular, 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 perform the Empirical Bayes (EB) shrinkage method on our SVA estimates on college outcomes for two main reasons, as suggested by Angrist et al. (2022). First, we focus on estimates for specific schools rather than averages. Second, the SVA on college outcomes is the dependent variable in our analysis rather than regressors. While we do not perform the EB, we weigh all our empirical exercises by the number of students, as SVA estimates are more precise for larger schools. By contrast, as we use SVA on learning as a regressor, we estimate by maximum likelihood the hyperparameters of the parametric normal model in Gilraine et al. (2020) and use the shrunk SVA on learning estimates in our empirical exercises.

5.2 Testing for Bias in School Value-Added Models

As the school value-added estimates of equation 10 rely on a selection-on-observables assumption to hold, we present two validation tests. 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 arising from the COAR mechanism. The second one is adapted from Jackson et al. (2020) to test for selection on unobservables.

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, then the quasi-experimental variation from the first-round offers should have perfect predictive power on the value-added estimates for COAR schools. For the set of schools in the COAR Network, $s \in COAR$, 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. Here, $\widehat{SVA}_j$ is the non-experimental estimate of the graduating high school value added from equation 10, and the rest of the variables are defined as in equations 4a and 4b. The first-stage coefficients γ_s describe the predicted effects of each COAR school offer on the non-experimental value-added measure. These coefficients are non-zero as long as COAR value-added estimates differ from those of counterfactual schools as COAR offers should 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 when the estimates of the empirical value added model (equation 10) predicts the effects of the school-specific offers from the COAR assignment mechanism. 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 Hausman-type test comparing the fuzzy multiple-instruments RDD estimates to the OLS value-added estimates from observational data.[12]

Table 9 reports the 2SLS estimates of equation 11a, suggesting that the SVA estimates of equation 10 align with the predicted COAR effects of the multiple-offers model. Column 1 reports the "forecast" coefficient with the associated standard error in column 2, and column 3 formally tests whether this coefficient is equal to 1 by reporting the p-value of such a test. Columns 4 and 5 report the over-identification test and p-value, and column 6 reports the first-stage F-statistics.

Overall, 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 in neither case is the over-identification test null rejected. While the estimates for top-10 enrollment seem less consistent, they are still aligned for top-10 private enrollment for which COAR offers have a higher predicted value, as shown by the first-stage F-statistic. A similar conclusion can be drawn for SVA on admissions and admissions mode by type of university. The test generally indicates that the SVA and the multiple-offers model are aligned for admissions at private universities (Panels B and C). While the forecast coefficient on exam admissions at top-10 private universities is not close to one, the test is reliable for extraordinary admissions, which are the ones that benefit specific secondary schools and for which COAR offers have a higher predictive power (first-stage F-stat of 48.96 vs. 23.71).

By contrast, the validation test in Panels B and D shows less alignment between the COAR multiple-offers model and the SVA estimates on public university admissions. As private universities, for which COAR offers also have more predictive power, rely more on special admissions to specific high schools, we focus our analysis on them. Estimates of the forecast coefficient in Table 9 contrast with the ones in Appendix Table A.9 that use "uncontrolled" averages of the outcomes at the school level as measures of SVA. For SVA that does not account for any covariates, the test rejects the forecast coefficient being equal to 1 for almost all outcomes except for exam admissions.

5.2.2 Testing for Selection on Unobservables

As COAR schools start in the third grade of secondary school, the test from equation 11a cannot be used to validate SVA on learning. For this reason, we also perform a similar test to the one by Jackson et al. (2020) to further test for selection on unobservables for both learning and college outcomes. In particular, we estimate the standardized effect of SVA on students' outcomes and test whether this estimate changes by controlling for other unobservable characteristics. We use the following estimating equation:

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

[12] 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.

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 value-added of school j on the student outcome.

We validate our SVA measures by showing the robustness of the estimates of ϑ_1 to two alternative models. The first is a 2SLS model where we use the SVA of the closest school to the family's residential address from the 2017 Census as an instrument for the SVA of student i's school. If the estimates of the OLS and 2SLS models differ, it would suggest that families select schools based on other criteria different from residential location, indicating that such unobserved preferences could bias our SVA estimates. The second strategy compares students within the same household who attend different schools by estimating equation 12 with household fixed effects and hence control for all unobserved characteristics at the household level.

Table 10 reports the estimates of equation 12 on learning and the main college outcomes of enrollment and admissions, while Appendix Table A.10 on admission modes for private and public universities. Column 1 reports the OLS estimate for all students, while columns 2 and 4 report this estimate for students with household locations in the 2017 census and those in households with children in multiple secondary schools, respectively. Column 3 reports the 2SLS estimate using the SVA of the nearest school, and Column 5 shows the estimate with household fixed effects. The general conclusion from this analysis is that the estimates of ϑ_1 are similar across the three samples and the three models for all outcomes, indicating little influence of unobservables in biasing the SVA estimates of equation 10.

5.3 SVA on College Outcomes: Reputation vs. Effectiveness

We next explore the link between SVA on college outcomes, effectiveness—measured by SVA on learning—, and reputation—measured by graduates' average characteristics—. If college admission authorities prioritize rewarding effective secondary schools for enhancing learning outcomes, there should be a positive relationship between SVA on college outcomes and SVA on test scores. Conversely, if these authorities primarily focus on the school's prestige or socioeconomic background, the average test scores and socioeconomic index would have a higher predictive power on SVA on college outcomes.

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

The following equation describes our estimating model:

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

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, respectively.

Figure 6 reports the estimates of equation 13 on SVA on college enrollment at private universities, with column 1 showing effects for all private universities and column 2 for top-10 universities. Panel A shows the relationship between SVA on test scores and these outcomes for two models. The red dots show the estimates of the vector $\boldsymbol{\delta}$ without any additional controls, while the blue dots show the effects after controlling for average scores and average socioeconomic index quantiles. Panels B and C report the analogous estimates of $\boldsymbol{\eta}$ and $\boldsymbol{\psi}$, the effects of average scores and socioeconomic index percentiles, respectively, with the red dots showing the estimates without additional regressors and the blue dots when the estimating model includes the three covariates. Figure 7 reports these same estimates for public universities.

Overall, the estimates in Figure 6 show that while there is a positive relationship between SVA on college enrollment at private institutions (for all universities and the top 10) and SVA on learning, such relationship disappears after controlling for the average scores and socioeconomic index. In fact, for the fully saturated model that includes the quantiles for the three variables, SVA on learning doesn't predict school effects on college enrollment at private universities. While the results in Panel B seem to suggest some predictive power of average achievement, the distribution of the average socioeconomic index score appears to have the largest predictive power in explaining SVA on enrollment at private universities. The difference between the top percentiles and percentile 1 of the average socioeconomic index is more than twice the difference between the top percentiles and percentile 1 of the average scores for all universities and around 1.5 times for top-10 private universities.

By contrast, the results in Figure 7 show that SVA on learning somehow predicts SVA on enrollment at public universities for all and top-10 institutions. While the evidence is inconclusive that higher SVA on test scores increases SVA on enrollment at public universities, most of the differences between SVA percentiles and percentile 1 are statistically different from zero, even in the model that includes the three regressors. On the other hand, estimates in Panel B show that average scores mainly predict SVA on enrollment at top-10 public universities, and the ones in Panel C that top percentiles of the average socioeconomic index reduce enrollment at public institutions, likely driven by students' application preferences. Appendix Figures A.6 and A.7 report the estimates on admissions at private and public universities, respectively, with similar conclusions to the ones on enrollment.

Next, we explore the same relation on SVA on extraordinary admissions at private universities in Figure 8. Similar to the effects on enrollment, the estimates show that SVA on learning doesn't predict extraordinary admissions at private universities after controlling for average scores and socioeconomic index. While average scores seem to predict SVA on admissions, such effects are small compared to the average socioeconomic index. Appendix Figure A.8 shows the relationship for exam admissions at private universities, which suggests that average scores predict this type of admission. As schools at the top of the socioeconomic distribution benefit the most from extraordinary admissions (percentiles 99 and 100), percentiles 75-98 and 87-98 predict exam admissions for all private and top-10 private universities, respectively.

As the estimates on admissions and enrollment combine students' preferences with university admissions policies, Figure 9 reports the estimates of equation 13 on eligibility for extraordinary admissions, abstracting from students' preferences. Column 1 shows the estimates on whether the school offers the IB program, and columns 2 and 3 on whether the school is on the list of preferred schools for top-10 and top-20 private universities, respectively. Overall, and similar to the conclusions on enrollment, the estimates show that SVA on learning has little predictive power on eligibility after controlling for average scores and socioeconomic background. While being at the top percentile of SVA on learning is predictive of offering the IB, such an effect is less than half of the top percentile of the average socioeconomic index. The results in columns 2 and 3 are even more striking as estimates of SVA on learning at the top percentiles are negative in the model that includes the three regressors. By contrast, while average scores and average socioeconomic index have similar effects on eligibility for extraordinary admissions at top-10 universities, the socioeconomic index is more predictive than average scores for top-20 private universities. Overall, this evidence suggests that universities mainly target the average socioeconomic background over average scores for extraordinary admissions, with both having more influence than SVA on learning.

5.3.1 Comparison of Eligible Schools for Extraordinary Admissions

We finalize this section by comparing the average characteristics and SVA of eligible schools 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. We determine schools as comparable in SVA on learning or average test scores by identifying those in the same percentiles of the distribution of these variables as the eligible schools for extraordinary admissions.

The comparison with the first two groups provides a similar conclusion to the previous empirical exercise: SVA on learning and even average scores have little influence on segregation in college access, and this is mainly explained by the socioeconomic background and primarily through extraordinary admissions. The comparison with COAR schools, on the other hand, shows that while the evidence of their effect on human capital is, at best, inconclusive, these schools provide talented low-income students with means to close the income gaps in college access.

Table 11 reports these differences for 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 report the standardized mean of the school group, columns 2 and 6 the difference with comparable schools in SVA on learning, columns 3 and 7 the difference with comparable schools in average graduates' scores, and columns 4 and 8 the difference with COAR schools. The numbers in columns 2-4 and 6-8 correspond to the difference in the variable between the respective group and the eligible schools for extraordinary admissions: IB schools (columns 2-4) and top-10 preferred schools (columns 6-8). Appendix Table A.11 reports the analogous differences for eligible schools on top-5 and top-20 private universities lists.

The results are consistent with the previous analysis: schools with graduates from a high socioeconomic background are the ones that benefit the most from extraordinary admissions, and SVA on learning or average scores play little role in explaining these differences. For instance, the differences in column 2 show that while comparable schools to IB schools in SVA on learning have lower average scores between 0.28 to 0.39σ, the difference in SVA on extraordinary admissions for private universities is between 4.8 to 6.4 times higher: 1.90σ lower for all and of 2.47σ lower for top-10 private universities compared to IB schools. A similar conclusion applies to comparable schools in average scores. Column 3 shows that these comparable schools have higher average scores in math and a difference of only 0.154σ in the average socioeconomic index. Still, there is a difference of 1.67 and 1.53σ of SVA on extraordinary admissions at all and top-10 private universities. While there are no differences in enrollment, this is explained by comparable schools having a higher SVA on exam admissions at private universities.

Finally, the differences reported in column 4 show that for top-10 private universities, COAR schools have a similar SVA to IB schools. First, COAR schools have graduates with higher average scores, and while there are still differences for SVA on enrollment at all private universities, such differences are small and not statistically significant for top-10 private universities, even for extraordinary admissions.

The conclusions for schools on the list of preferred schools for top-10 universities are similar. Overall, comparable schools in SVA and average scores have lower SVA on enrollment at all and top-10 private universities, with such differences larger for extraordinary admissions. By contrast, despite COAR schools having a lower average socioeconomic index, they have similar SVA on enrollment at top-10 private universities and even a higher SVA of 1.84σ on extraordinary admissions. The differences for schools on the list of preferred schools for top-5 and top-20 private universities in Appendix Table A.11 result in the same conclusions.

6 Conclusion

This paper explores the relationship between secondary 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' high ability levels.

We further complement this story by estimating SVA models on test scores and college outcomes for most secondary schools in Peru. We fist validate these SVA estimates by providing two validation tests. First, we leverage the COAR assignment, finding consistent effects from this quasi-experimental variation with the observational SVA estimates. Second, we show that the relationship between SVA estimates and student outcomes is similar after controlling for unobservable factors.

We estimate the relationship between SVA on college outcomes, SVA on learning, and average graduates' characteristics. Our results show that after accounting for average scores and socioeconomic background, SVA on learning has little predictive power on school effects on college outcomes, with the average socioeconomic index of a school explaining most of the variation in these effects at private universities, mainly through extraordinary admissions. Moreover, due to their reputation, even if COAR schools do not generate significant human capital gains, they have a similar or larger SVA on enrollment and extraordinary admissions to top private universities than other eligible schools for these exceptional admissions. Hence, COAR schools provide talented low-income students with a signal that reduces income gaps and segregation in college access.

Overall, the results show that without the information conveyed in test scores, college admission authorities weigh more alternative information sources, including the reputation of the graduating school. Moreover, such reputation effects appear to be highly related to a school's average socioeconomic background. These findings suggest that the current debate around the distributional consequences of standardized tests in college admissions should contrast the potential bias in test scores with the persistent gaps that could result 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%.

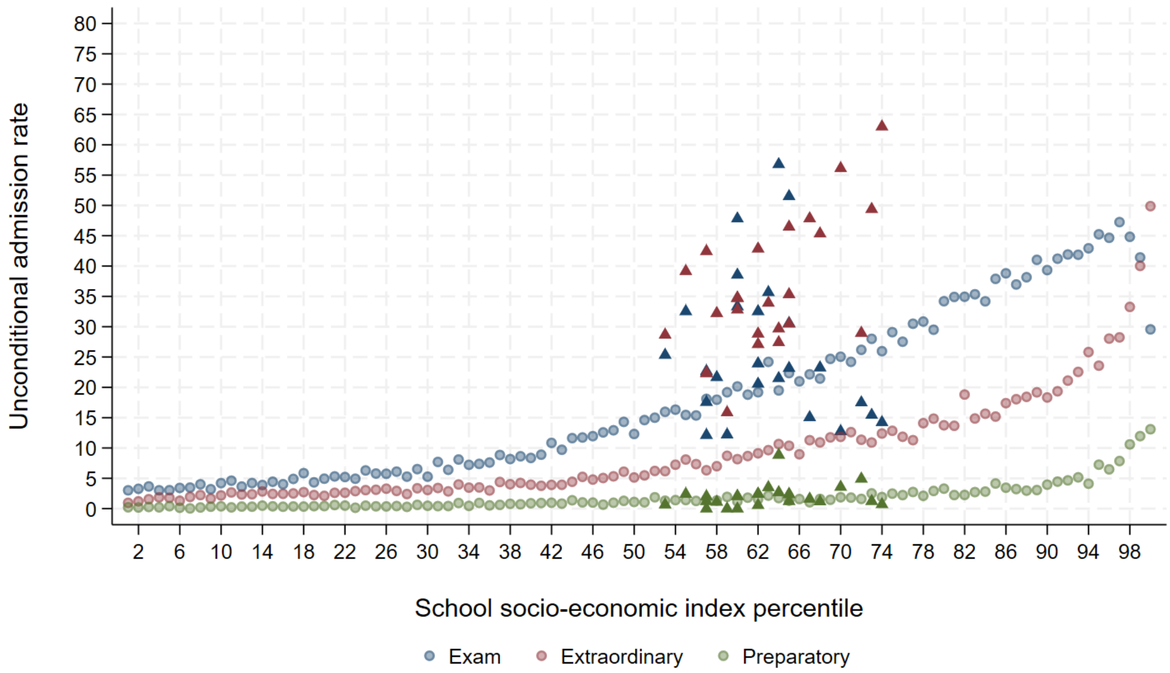
Table 11: Eligible Schools for Extraordinary Admissions vs. Comparable Schools in SVA on Learning, Average Scores, and COAR Schools

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

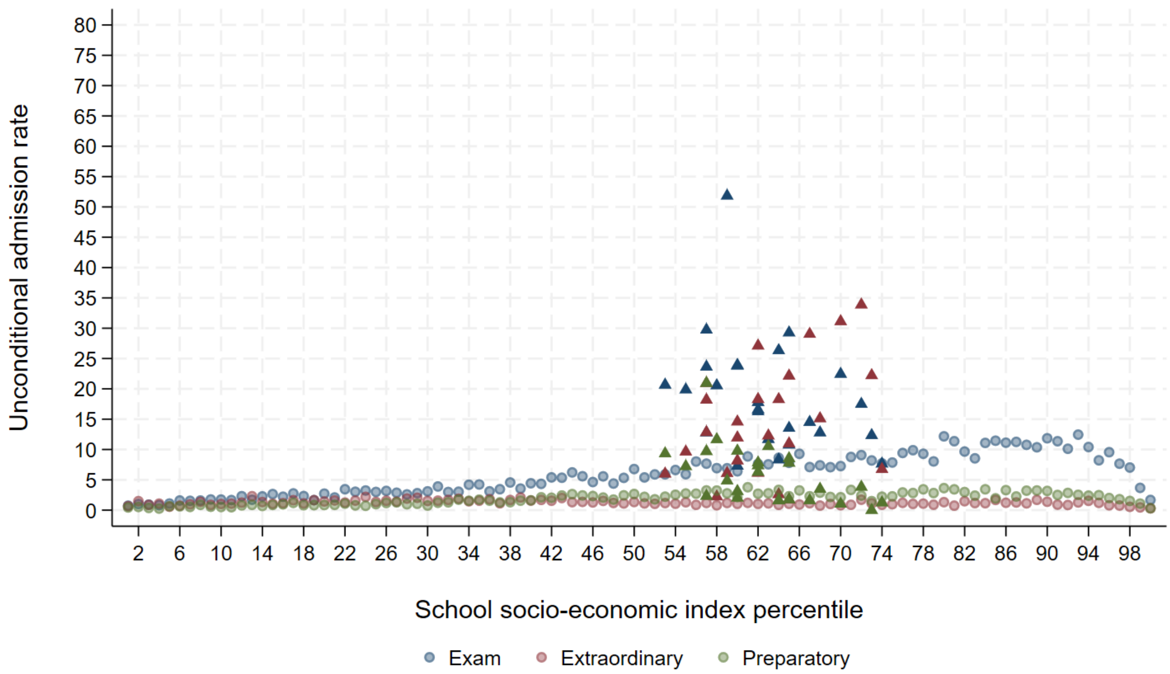
Notes: This table reports differences between schools eligible for extraordinary admissions and comparable schools in SVA on learning, average graduates' scores, and COAR schools. Columns 1 to 4 report differences for schools offering the IB program and columns 5 to 8 for schools on the list of preferred 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

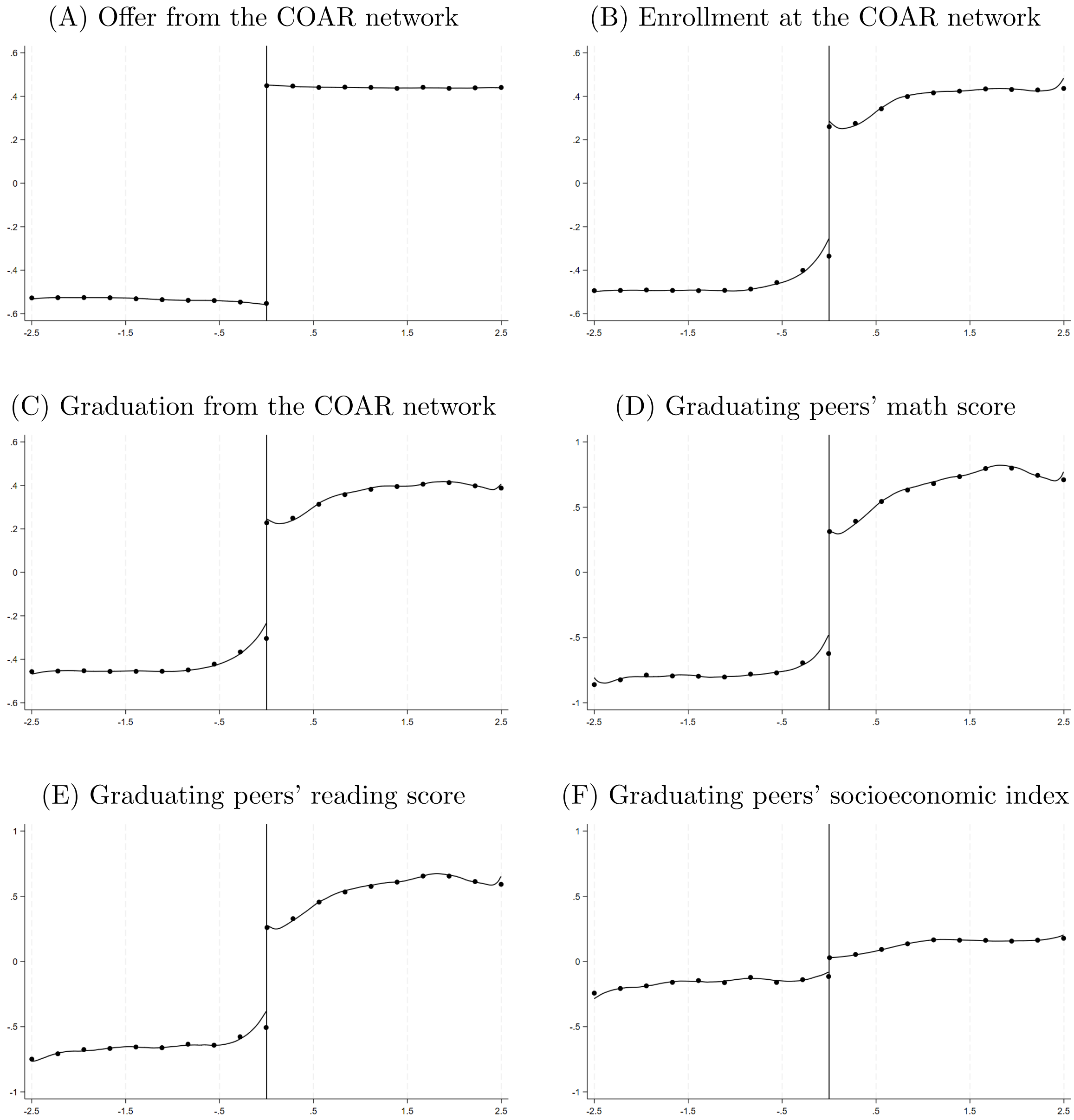


(B) Public universities



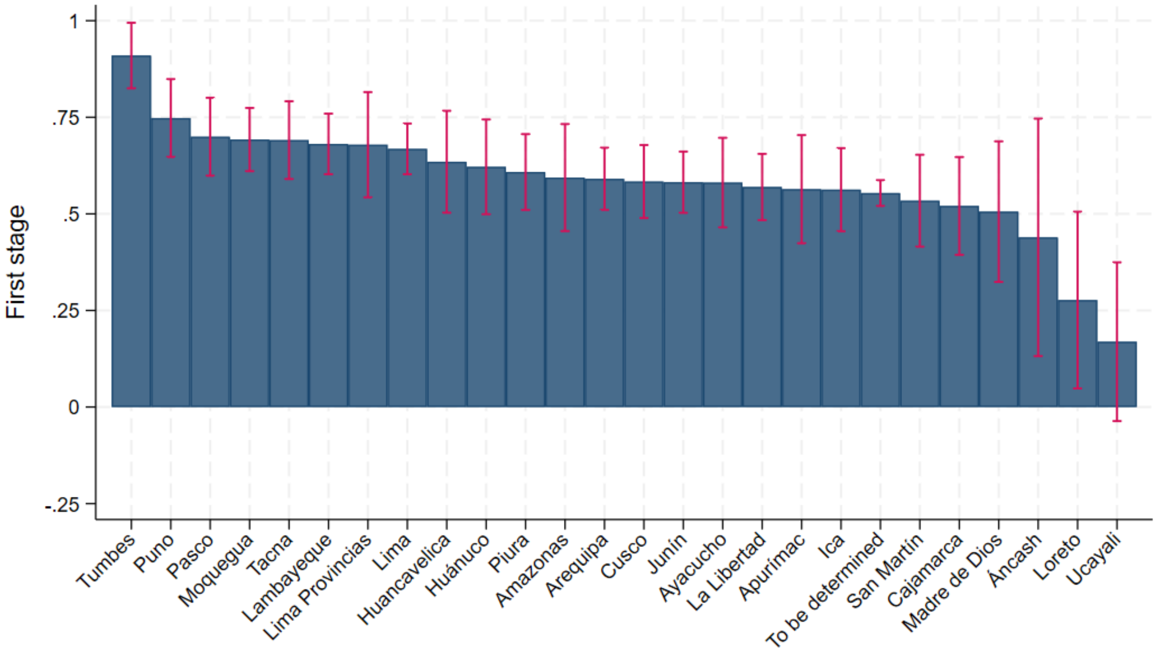
Notes: This figure shows the unconditional admission rate for three different admission modes over the percentiles of the average school socioeconomic index. Panel A plots these rates for private universities, and panel B for public universities. Triangle markers represent COAR schools, while circle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

Figure 2: COAR Network First Stage



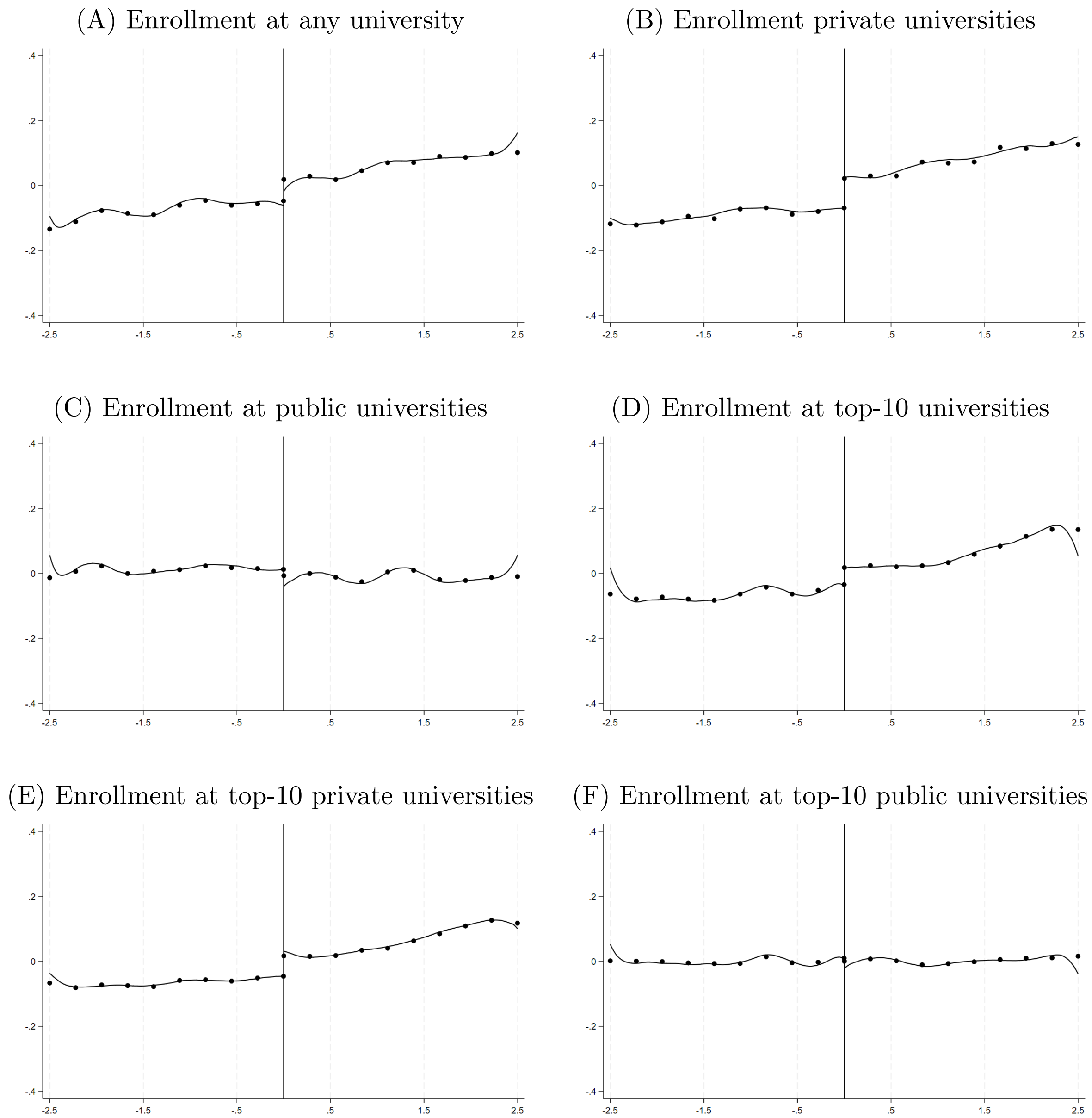
Notes: This figure plots six first-stage outcomes near the region-specific qualifying cutoffs against the COAR Network school running variable. All outcomes are plotted after partialing out risk sets. The black dots represent the bins of the outcomes in different values of the running variable; lines 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



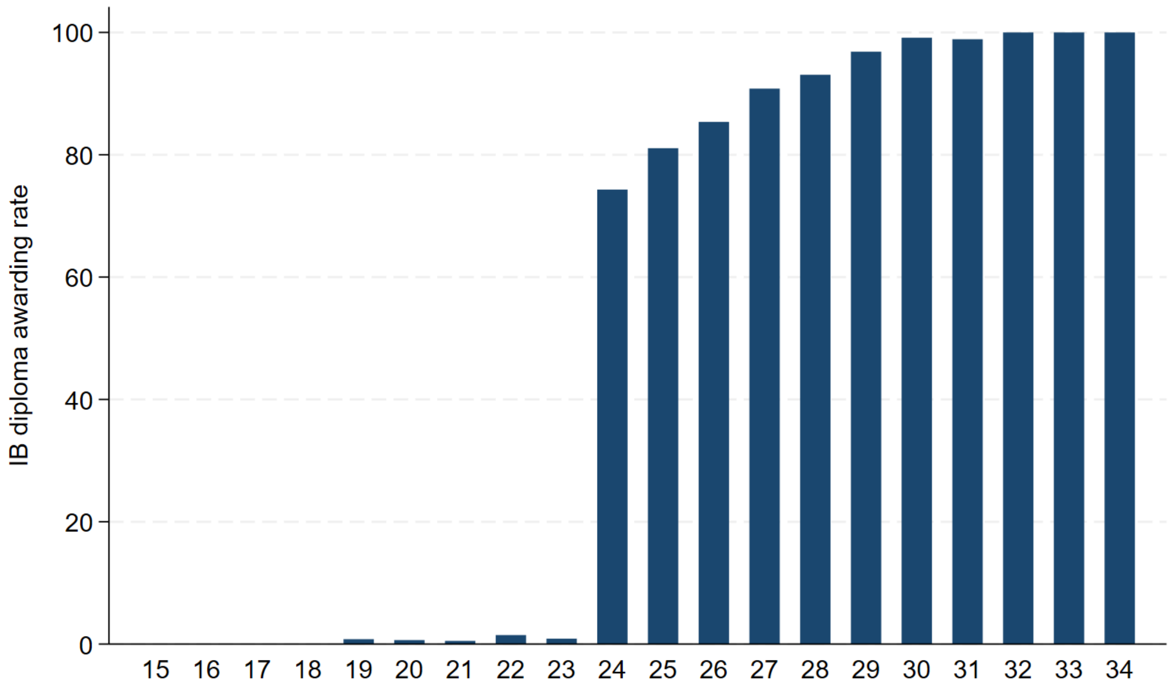
Notes: This figure reports estimates of the first-stage effects of individual COAR school offers on COAR graduation using the multiple-offers model. Whiskers mark 95% confidence intervals.

Figure 4: COAR Network Reduced-Form Effects



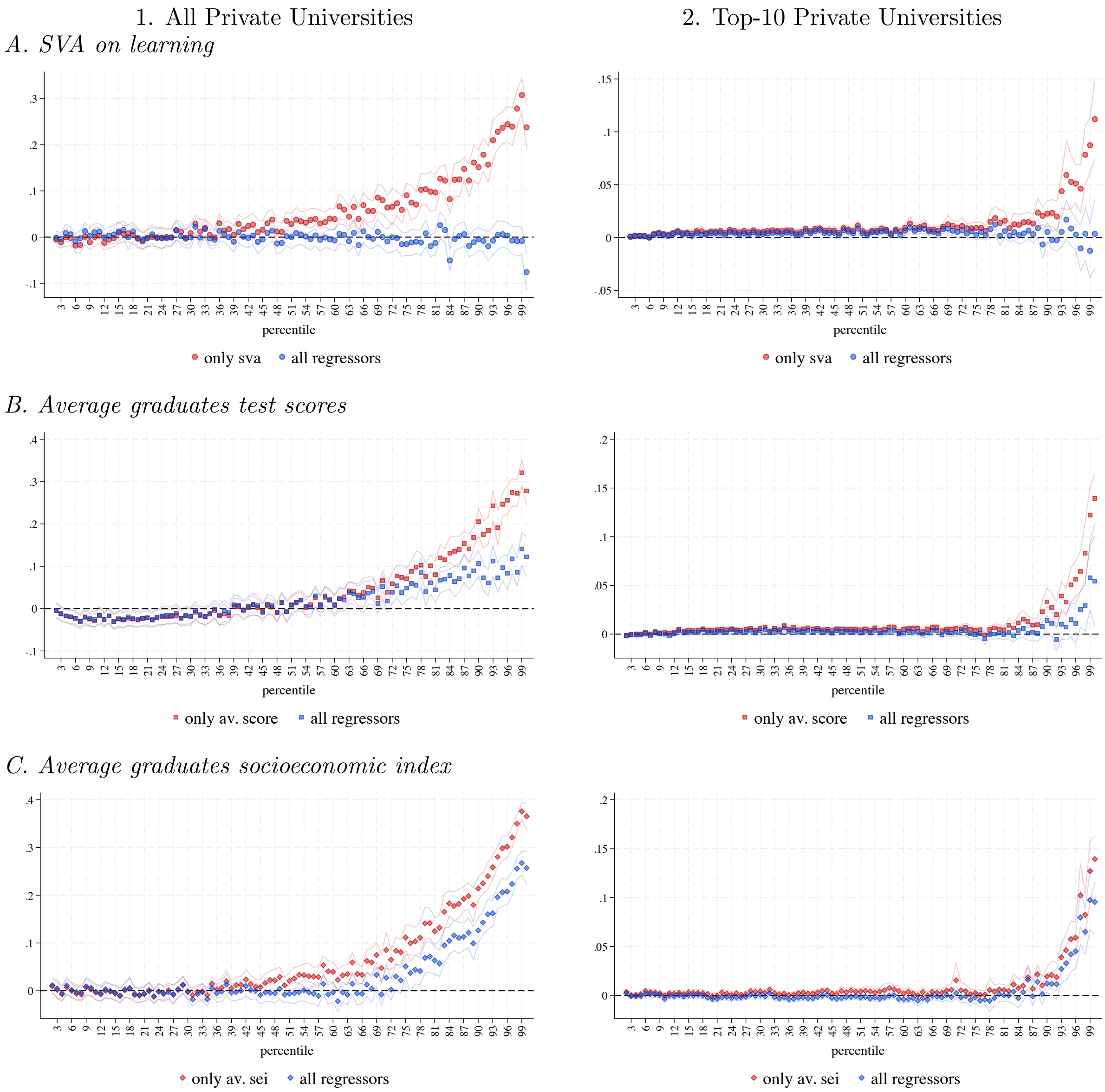
Notes: This figure plots six university enrollment outcomes near the region-specific qualifying cutoffs against the COAR Network school running variable. All outcomes are plotted after partialing out risk sets. The black dots represent the bins of the outcomes in different values of the running variable;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

Figure 5: International Baccalaureate First Stage



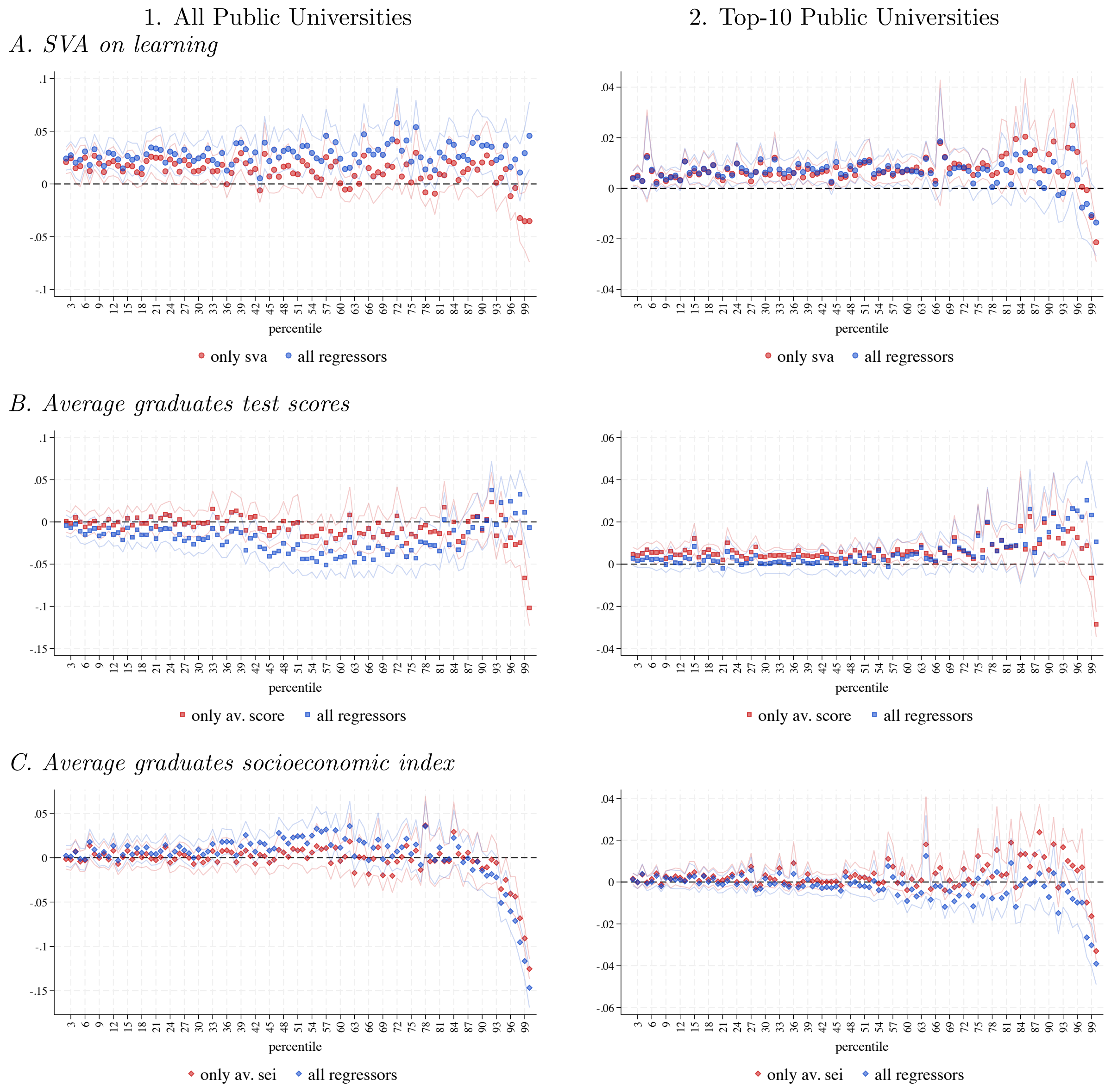
Notes: This figure shows the likelihood of receiving the IB Diploma at different values of the final score in the IB Program. Our estimates in Table 8 compares students who scored 23 vs. those who scored 24 points.

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



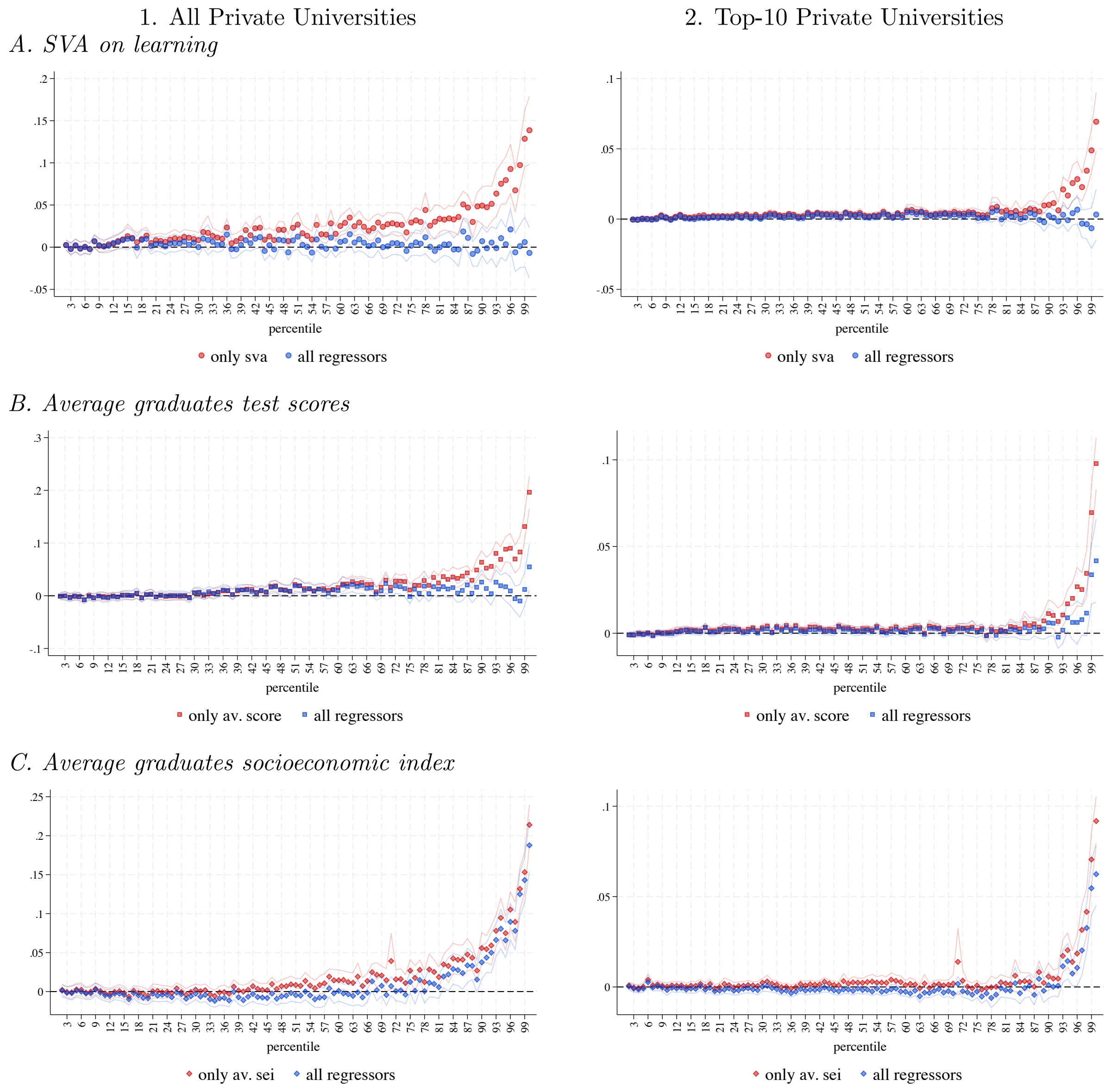
Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college enrollment at private universities. Column 1 reports the effects for all private universities, and column 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



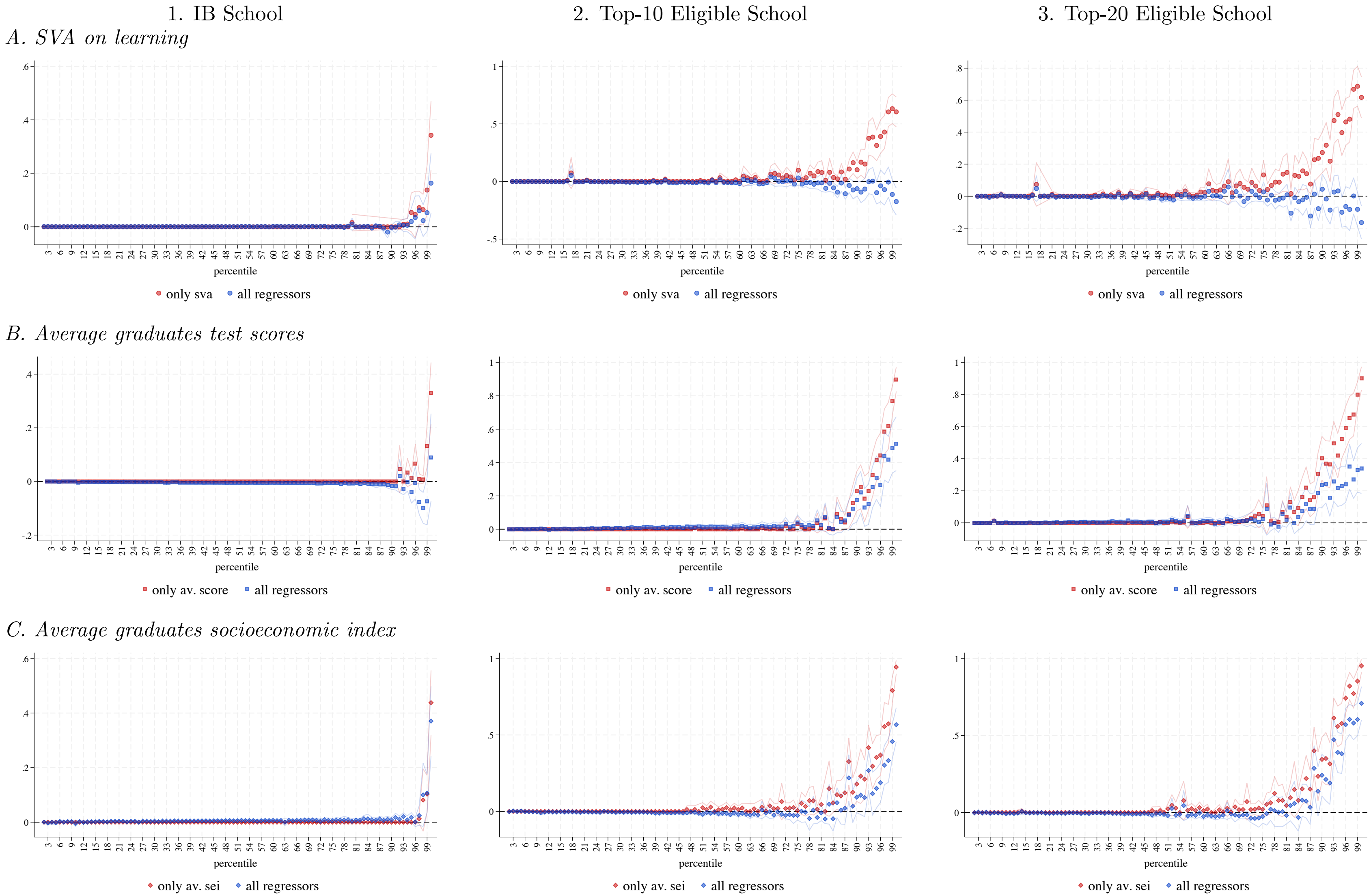
Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college enrollment at public universities. Column 1 reports the effects for all public universities, and column 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	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	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

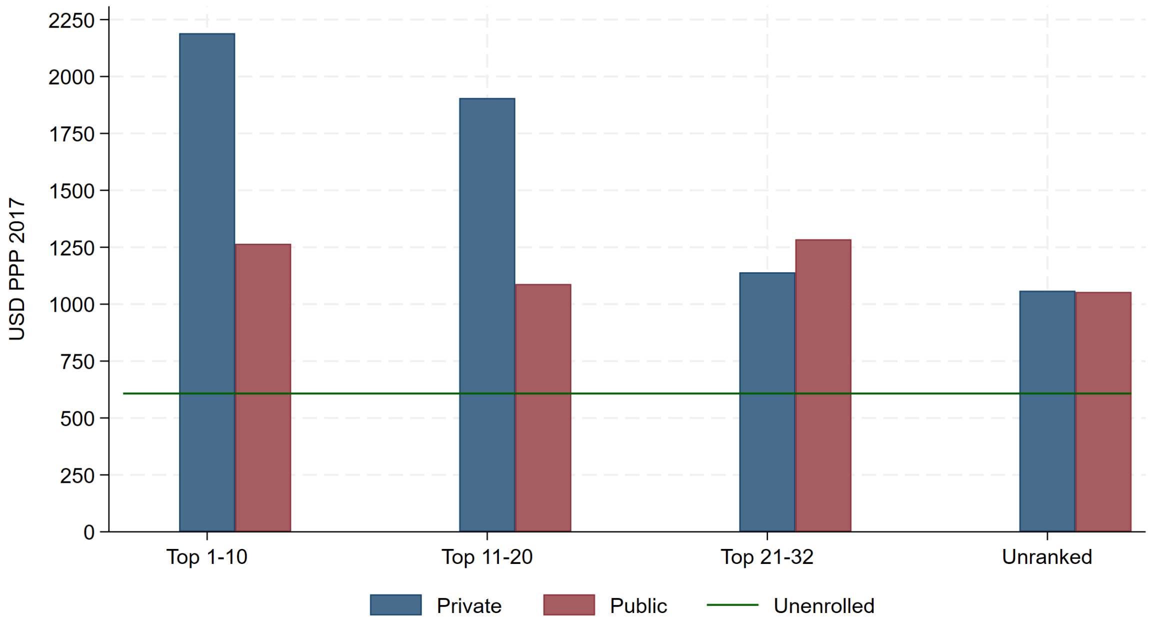
UNIVERSIDAD DEL PACÍFICO

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

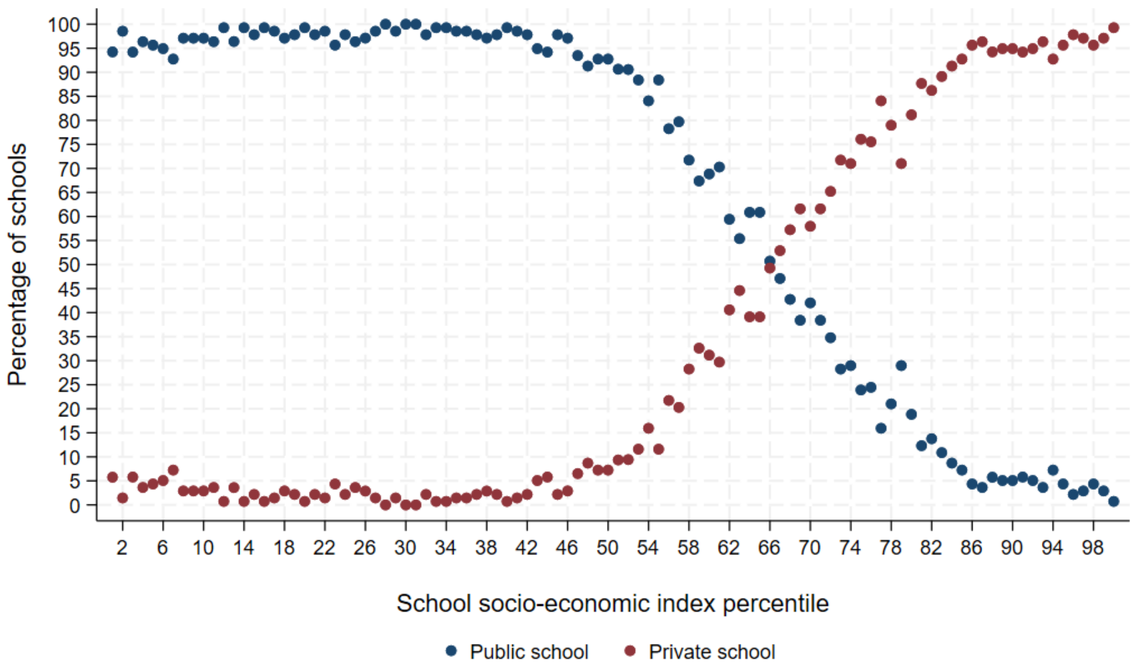
Notes: This figure shows a sample of Universidad del Pacífico's list of preferred schools for its 2022 admission process.

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



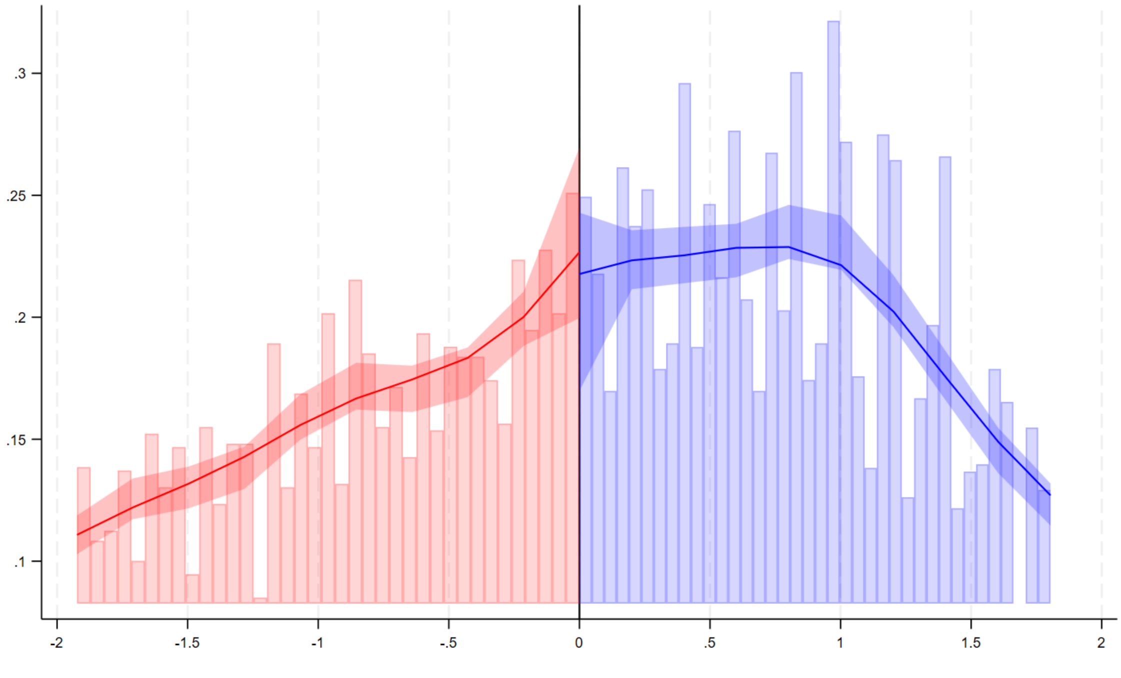
Notes: This figure plots the average monthly wage of graduates in 2019 by type of university and ranking according to a portal designed by the Ministry of Education to provide information about existing programs to college applicants. We use the average wage of high school graduates, as reported by the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

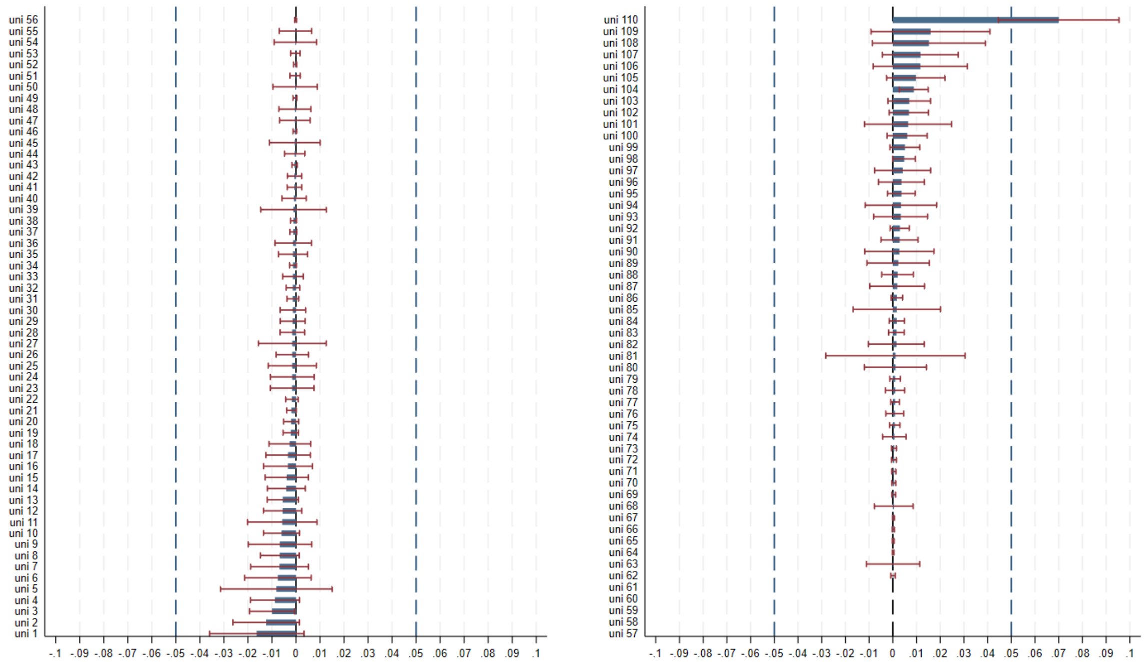
FIGURE A.4: Manipulation Test



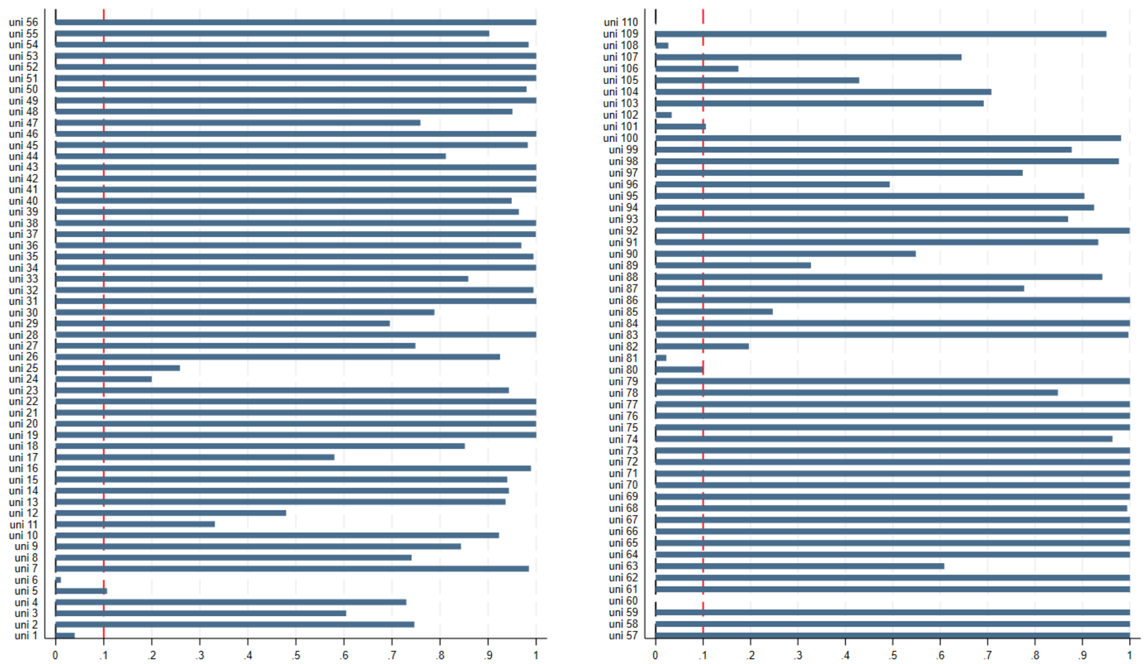
Notes: This figure reports the manipulation test proposed in Cattaneo et al. (2018). The p-value of the manipulation test is 0.277.

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

(A) Single-offer model

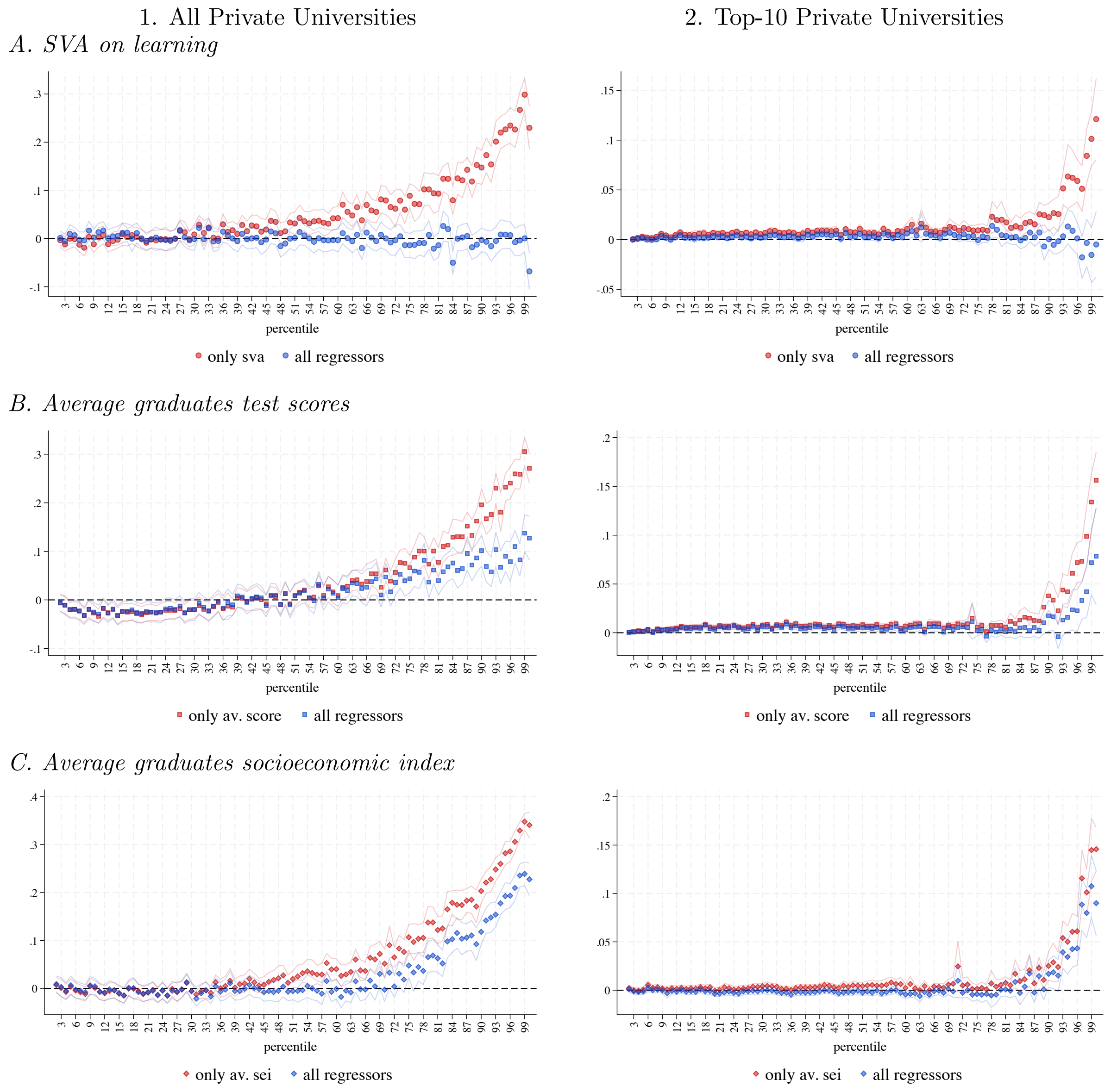


(B) Multiple-offers model



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



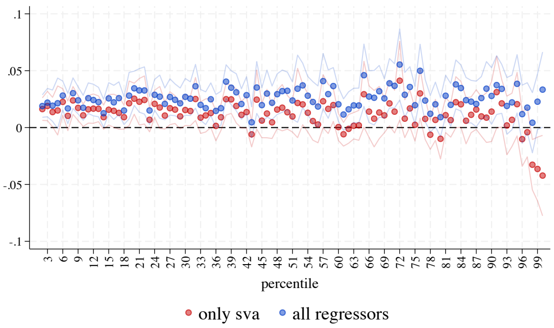
Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college admissions at private universities. Column 1 reports the effects for all private universities, and column 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.

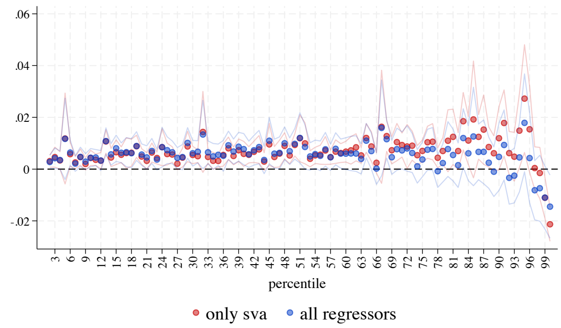
Figure A.7: SVA on College Admissions at Public Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics

1. All Public Universities

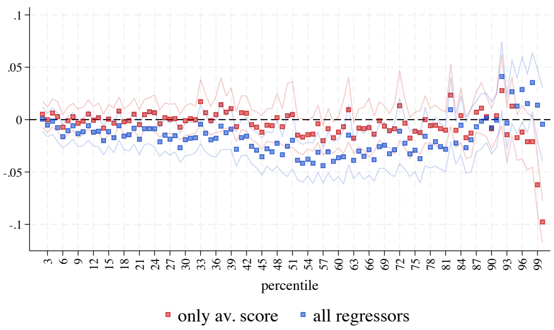
2. Top-10 Public Universities

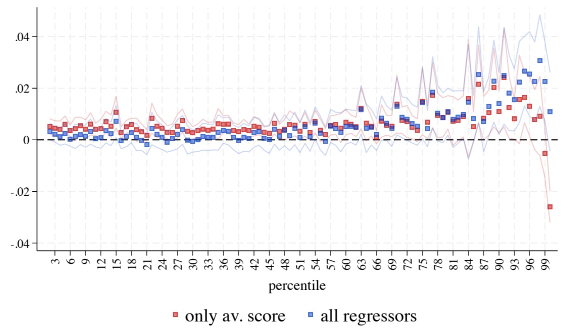
A. SVA on learning



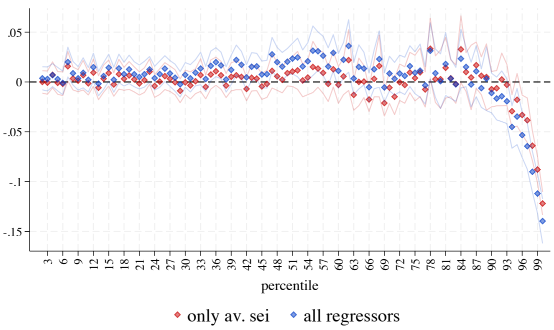


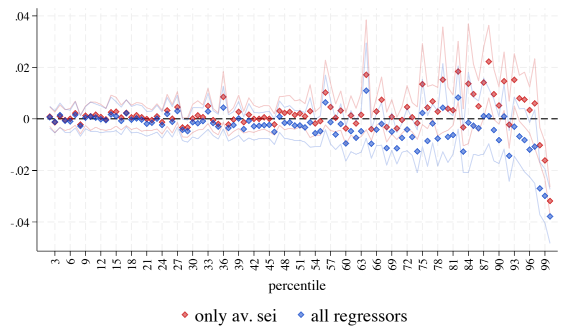
B. Average graduates test scores





C. Average graduates socioeconomic index



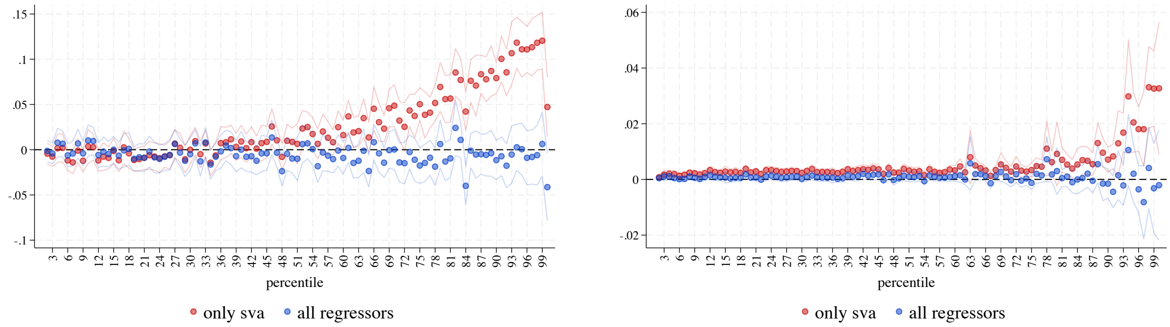


Notes: This figure reports the estimates of equation 13, the relationship between the percentiles of SVA on learning, average graduates test scores, and average socioeconomic index on SVA on college admissions at public universities. Column 1 reports the effects for all public universities, and column 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.

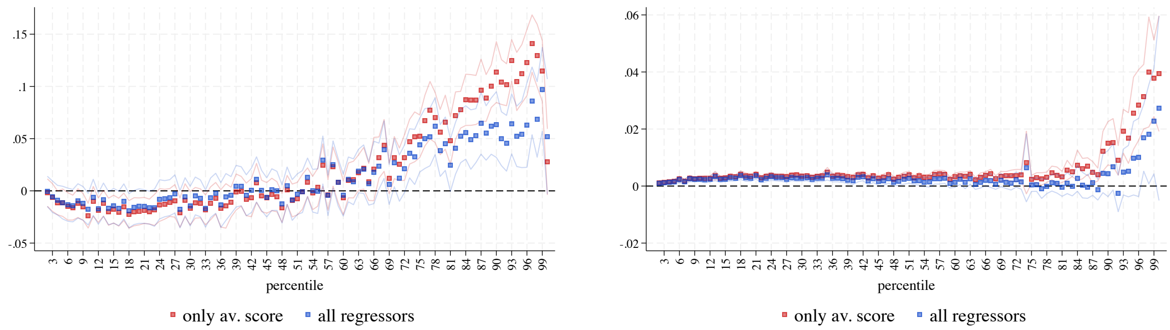
Figure A.8: SVA on Exam Admissions at Private Universities vs. SVA on Learning and Secondary School Graduates' Average Characteristics

1. All Universities 2. Top-10 Universities

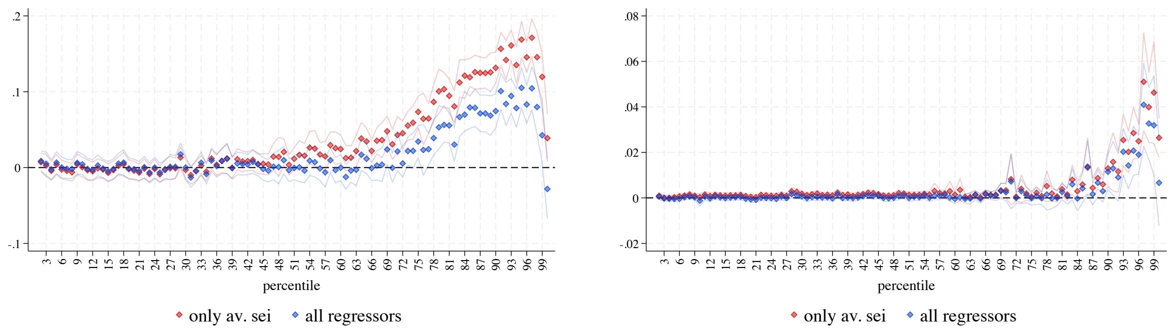
A. SVA on learning



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 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 High Schools Sample

In this section, we detailed the construction of the *All High 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.

C.1 Steps of the Assignment Mechanism

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

In the first step, the government assigns slots any COAR offers by determining the number of COAR slots available to each region. Let $\tilde{q}_l$ denote the number of slots assigned to region l, with $Q = \sum_{l \in \mathcal{L}} \tilde{q}_l$, which determines general COAR offers for each region. 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. As described in the main text, 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 as they 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 government assigns 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: $v_s = q_s - |i \in \mathcal{I} : \ c_{1i} = s, \ r_i \leq \tau_1(w_i, s)|$. 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:[1]

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

Step 3: Assignment of 2nd-round offers

While we do not use second-round offers in out research design, the process works as follows.

[1] The characterization of the three cutoffs, τ_0, τ_1, and τ_2, assumes more applicants than available seats at each stage, which may not always hold empirically. For instance, in some cases, applicants' second choice can be undersubscribed at stage 2.2., allowing all of them to receive a 2nd-choice offer. The matching function accommodates such cases by equating the relevant cutoff to the minimum score among the considered applicants. We also assumed a positive quantity of available seats at each step, which may not always hold. For example, it may be the case that after step 2.1., there are no longer seats available in an applicant's second choice when all the other-region slots are assigned as a 1st-choice offer to applicants from other regions. Such cases are equivalent to setting the relevant cutoff, in this case, $\tau_2(c_{2_i})$, to the maximum score of the considered applicants.

First, 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 either 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, 1] with continuously differentiable cumulative distribution F^i, where running variables for applicants i and j 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.

As described in Section 4.1, for each applicant, the COAR mechanism derives into three cutoffs τ_0, τ_1, and τ_2, that determine the assignment rates at any COAR school and each specific school in the network. 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 $\pi_{s,i} = \mathbb{E}[D_{s,i} = 1 | \theta_i = \theta]$ 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:

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

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 $\mathbb{E}[D_{s,i} = 1 | \theta_i = \theta, D_i = 0] = 0$, then:

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

with $\tilde{\pi}_{s,i}$ denoting $\mathbb{E}[D_{s,i} = 1 | \theta_i = \theta, D_i = 1]$: 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:

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

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

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 $lim_{x \to 0} \frac{f_x(x)}{g_x(x)}$ and $lim_{y \to 0} \frac{f_y(y)}{g_y(y)}$ 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:

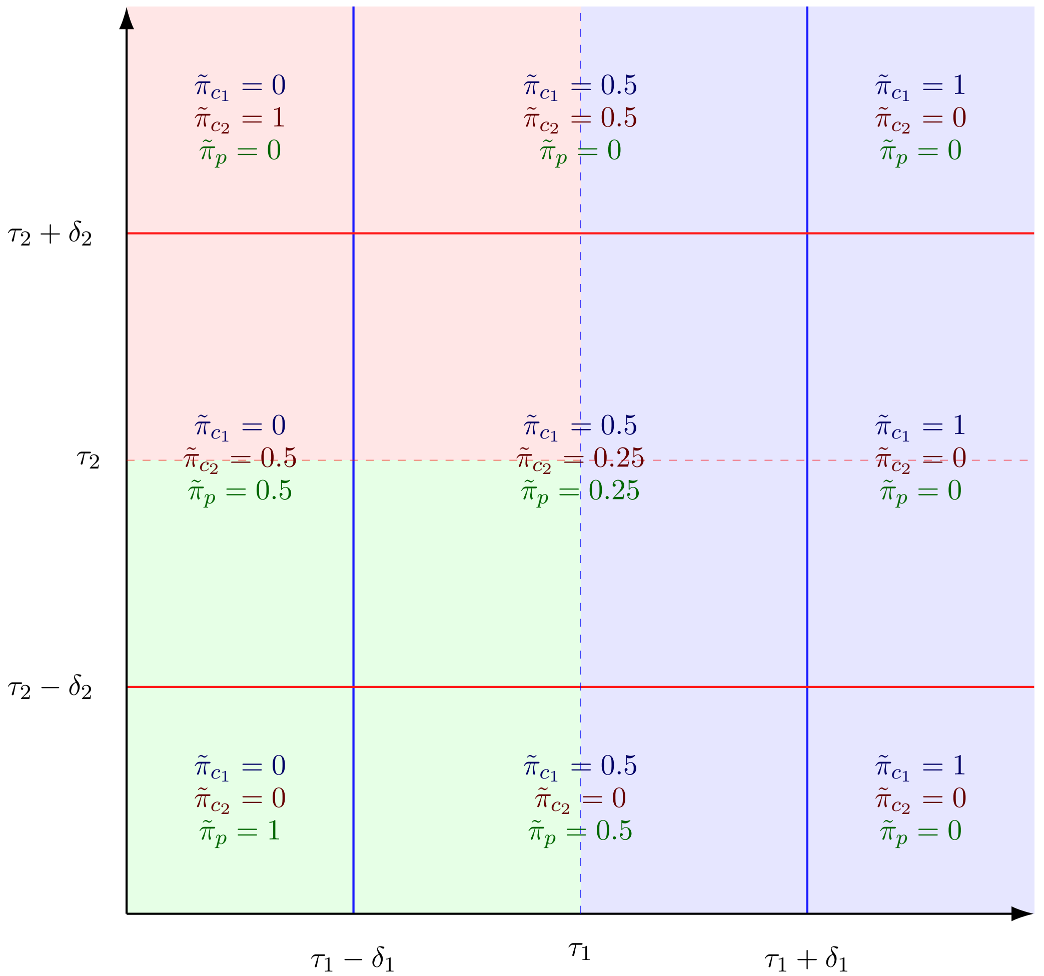
$$\tilde{\pi}_{p,i} = \begin{cases} 0 & \text{if} \quad \begin{array}{l} r_i > \tau_1(w_i, c_{1_i}) + \delta_1 \quad \text{or} \\ r_i > \tau_2(c_{2_i}) + \delta_2 \end{array} \\ \frac{F_{w,c_1}(\tau_1) - F_{w,c_1}(\tau_1 - \delta_1)}{F_{w,c_1}(\tau_1 + \delta_1) - F_{w,c_1}(\tau_1 - \delta_1)} & \text{if}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

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:

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

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.