“Peer Models”: Does the admission of high school students encourage younger peers to apply for a flagship university?*

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Abstract

The difference in higher education access among students from high and low socioeconomic status is substantial worldwide, and part of it comes from the initial gap in university applications. We test if the presence of role models plays a role in the post-secondary application of younger peers. Specifically, we evaluate if the new admissions of high school students into UNICAMP, one of Brazil's most selective universities, encourage younger peers from the same high school to apply to the university. We find that schools with students barely above the university admission cutoff increased their applications the following year. However, the effect is significant mostly for students from private schools. We show that these students apply more not only to UNICAMP following the admission of an older peer, but also to other public universities, and we find larger effects the closer (in terms of school year) the younger cohort is to the older peers admitted to the university. The only scenario where public high school students react by applying more is when their older peers are admitted to the least competitive majors.

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1 Introduction

Despite many recent efforts to address the differences in higher education access between students of high and low socioeconomic status, the gap in post-secondary applications remains substantial. Those differences are particularly relevant in the most selective institutions, even among high-achieving students (Altmejd et al., 2023; Hoxby and Avery, 2012). There are many reasons to explain the contrast in application behavior in the literature. For example, students from disadvantaged backgrounds might be applying less to flagship universities because they have tighter budget constraints (Dinkelman and Martínez, 2014; Pallais, 2015; Solis, 2017) or are less informed about the admission systems and future labor market returns (e.g. Busso et al., 2017; Black et al., 2015; Hastings et al., 2015, 2016; Hoxby and Turner, 2015; Oreopoulos and Dunn, 2013).

However, students may face other non-financial barriers in transitioning to college. Present bias, lack of encouragement, and low expectations regarding post-secondary education, among other behavioral constraints, can also interfere with the decision-making process (e.g. Dynarski et al., 2021, 2023; Lavecchia et al., 2016). Inspirational factors, such as the presence of role models, might also play a role. Chung (2000) develops a model that examines the phenomenon as an 'informational' device, where role models disclose useful information about the present value of current decisions. Role models could either improve students' confidence in succeeding or diminish the uncertainty about the future payoffs of pursuing a post-secondary path (Delaney and Devereux, 2020).

In this paper, we evaluate if older peers who succeeded in getting accepted to a flagship university can act as role models to younger students. Specifically, we test if the admission of high school students encourages younger peers from the same high school to apply for one of Brazil's most selective universities (UNICAMP) the following year. Throughout the paper, we also investigate if the effect varies by public and private high schools to understand the differences between students from different backgrounds.

We use the comprehensive application records of UNICAMP between 1990 and 2018, merged with schools' information from the Brazilian School Census and ENEM (*Exame Nacional do Ensino Médio*) public database. We also exploit the admission records from the other two State flagship universities (USP and UNESP) for a brief period.

There are at least two main empirical challenges. First, we need to disentangle our potential encouragement effects from school unobservable factors and the influence of same-year peers' characteristics that might affect the application decision. Second, we must be able to compare high schools with the same admission record to the university, to avoid confounding effects related to the school quality/orientation toward post-secondary education. Ideally, an older peer's admission to the flagship university should be the only feature that changes among the schools we contrast and that brings the attention of the younger cohorts to the university.

To overcome these issues, we employ an RDD approach, which tests whether, in high schools whose students were admitted into UNICAMP for the first time barely above the cutoff grade, there is an increase in subsequent applications of younger peers – relative to the high schools with students barely below the university cut-off (and that remained without any admissions). We find that schools with students barely above the university admission cutoff increased their applications by 0.5 the following year, relative to the counterfactual group, equivalent to more than a third of the average number of applications for those schools.

When we split the sample between public and private high schools, we find that only private high schools with the first (barely) admission to UNICAMP drive the overall effect. These schools increased their applications by 0.4-0.6 the following year, equivalent to almost 40% of the schools' average number of applications to the university.

The effects are not restricted to UNICAMP applications only. Exploiting a question from the applicants' survey – which asks the candidates what other universities they would apply to besides the UNICAMP – we report that, following a peer's admission to UNICAMP, the next immediate cohort applies more to other public universities as well. This is consistent with the fact that this new event – the admission of an older peer – not only encourages the application to this specific flagship university but 'opens' a broader set of possibilities in terms of a post-secondary education path.

We also investigate the mechanisms behind our effects. Firstly, we assess if some conditions related to the spread of information play a role in explaining the patterns we observe. Specifically, we examine whether the effects are heterogeneous regarding high school location, high school size, and the introduction of an affirmative action policy (AA) in the university. While the school location and size could be directly associated with the amount of information about a former student's admission, the AA – which gave additional points to public high school students in the university exam – could have changed the general information about the admission probability between public and private students, then affecting the relevance of the older peer admission in our context.

The heterogeneity analysis shows that only students from schools located in the same state as the university are affected, but school size does not seem to change the salience of the new admissions. As before, only private schools drive those differential effects. In addition, the students from private high schools were influenced by the admission of older peers only in the absence of affirmative action, but the policy did not change the 'peer model' effect for public high students, which remained insignificant. However, these results are noisy and we cannot perfectly point out the importance of these informational mechanisms. Still, we anecdotally show that public and private schools behave very distinctively concerning post-secondary education and the information about their students' admissions to universities.

Secondly, we evaluate if the effects vary according to role model proximity. We show that they intensified relative to the baseline results when the older peer is only one school year ahead, i.e. when we restrict the potential 'influencers' to be those who just concluded high school. These results are consistent with more pronounced effects when social links are stronger or the probability of learning about older peers' outcomes is higher (Altmejd et al., 2021; Barrios-Fernández, 2022). However, we observe this pattern mainly in the private schools.

Yet, why do we not find any effects for public high school students? When we consider another measure of proximity, based on the grades in an independent exam used as an admission test for other public universities (ENEM), we find that the distance in test scores from the potential 'influencer' is much bigger for public high school students than for private high school ones. This, in turn, could explain why we do not see an increase in applications in the former group.

Then, we investigate if there are any differential effects according to the majors that the older peers are accepted. Public high school students only apply more to the university when their older peer is admitted to the least competitive majors, whereas private high school students do so when their older peers are admitted to the most competitive ones. This finding suggests that for a role model to be effective, it should not only be 'closer' socially, but also in terms of possible future achievements – what the role model accomplished must be 'achievable' from the perspective of the younger student.

Additional exercises show that results are robust to different specifications and that the effects are not driven by students who were applying to other universities in the first place, but were rather 'newcomers' in terms of post-secondary application. Moreover, we test if the effects persist if we consider a sample of schools (a) with no past admissions in the last three years and (b) regardless of past admissions. Although some caveats may apply in those comparisons, we find that our conclusions remain the same for the former sample but there is no evidence of any effects for the latter. This provides suggestive evidence that role models are more important in contexts where the admissions are unique or rare, and thus more salient to the younger ones.

Lastly, we examine if the additional applications turn into university access. We do not find any positive or negative evidence when it comes to longer-term outcomes, such as admission, enrollment, conclusion, or dropout. Hence, the admission of older peers encourages the next cohort (of private high school students) to apply, but the encouraged students do not get into the flagship university.

As far as we are concerned, only a few papers try to address the effects of older peers' admission on application to higher education. The most related paper is Barrios-Fernández (2022), which exploits a threshold eligibility rule for student loans in Chile. It shows that having a close neighbor marginally qualifying for a student loan and attending a university significantly increases the university enrollment of younger potential applicants one year later. In the author's setup, the effects become weaker with geographical distance and decay with differences in age and socioeconomic status. In another related paper, Allende-Labbé et al. (2023) studies a program that gives preferential access to colleges in Chile and also shows that the marginally eligible candidates increase university attendance of younger close neighbors. However, isolating the peers' admission effects from the influence of the educational environments that the admitted ones share with the younger potential applicants is still challenging, even in their framework.

Besides adding to the literature on the determinants of applicants' behavior in general, we also refer to the literature on role models in higher education (e.g. Borges and Estevan, 2024; Carrell et al., 2010; Fairlie et al., 2014; Hoffmann and Oreopoulos, 2009) going beyond the impacts of same-gender and same-race professors on future educational outcomes. In addition, we contribute to the stream of literature addressing peer effects in post-secondary education, which usually exploit exogenous allocation of roommates (e.g. Boisjoly et al., 2006; Carrell et al., 2019; Corno et al., 2022; Griffith and Rask, 2014; Sacerdote, 2011) or sibling spillovers in major choice and college application (e.g. Aguirre and Matta, 2021; Altmejd et al., 2021; Goodman et al., 2015), but instead of focusing on simultaneous or within family interactions, we are dealing with more distant relationships where different mechanisms might be taking place.[1]

[1] We also slightly contribute to the literature on affirmative action effects (e.g. Allende-Labbé et al., 2023; Assuncao and Ferman, 2015; Estevan et al., 2019a,b; Francis and Tannuri-Pianto, 2012; Mello, 2022, 2023; Oliveira et al., 2023), in the sense that we exploit whether a particular AA policy would be related to an informational mechanism of our effects.

The remainder of the article is organized as follows: Section 2 provides a brief institutional background of the UNICAMP and details the university admission system. In Sections 3 and 4 we describe our data and the empirical strategy, respectively. Section 5 describes the validity of the regression discontinuity design in our setting. Section 6 reports our main findings, and in Section 7 we address possible mechanisms that might be in action. Section 8 shows robustness checks for the empirical strategy and alternative estimations. Section 9 provides additional results regarding longer-term outcomes. Section 10 discusses the implications of our findings. Lastly, Section 11 concludes our paper.

2 Institutional Background

2.1 UNICAMP's relevance and the application gap

In Sao Paulo State, there are three research-intensive public universities widely known as the most important in the country - *University of São Paulo* (USP), *Universidade Estadual de Campinas* (UNICAMP), and *Universidade Estadual Paulista 'Julio de Mesquita Filho'* (UNESP). Together, they admit more than 20,000 students every year, and no tuition is applied. UNICAMP alone is responsible for 7-10% of Brazil's research and represents almost one-third of the total number of applications to the State's universities.[2] Students are free to apply to any of the three universities – In fact, Estevan et al. (2019a) reports that almost one-third of applicants to USP (UNICAMP's major competitor) also applied to UNICAMP in 2004.

However, even though more than 85% of the State's high school enrollments are publicly provided,[3] public high school students only account for a small portion of applicants at these universities. Figure 1 shows that the share of public students applying to UNICAMP is slightly more than 30%, representing a 22k absolute application gap relative to private high school students in 2018.

The public-private application gap is also manifested in terms of the number of 'sending schools': public high schools that have at least one of their graduates applying to UNICAMP represent around 40%, but on average, "send" half the number of

[2] See more details on https://www.prp.unicamp.br/pesquisa-na-universidade/ and https://www.comvest.unicamp.br/ingresso-2024/vestibular-2024-2/vagas-por-curso-e-perfil/). UNICAMP is usually the country's second most highly ranked in international rankings (USP is usually the 1st, and UNESP the 3rd - https://www.timeshighereducation.com/world-university-rankings.

[3] Enrollments for SP State are similar to national parameters. See more details for SP State in https://qedu.org.br/uf/35-sao-paulo/censo-escolar. For national parameters, see INEP (2021).

applicants compared to private high schools (Figures 2).[4]

More importantly, not only is the application gap huge, but it has widen over the time we analyze, and it did not seem to change its pattern after the introduction of the university's affirmative action (AA) in 2005.[5] Although there is already causal evidence of AA shifting *admission* towards minorities and public high students in other public flagship universities in Brazil (Assuncao and Ferman, 2015; Francis and Tannuri-Pianto, 2012; Oliveira et al., 2023), and particularly in UNICAMP (Estevan et al., 2019a,b), it is still unknown what drives the *application* behavior – these studies are usually interested in admission effects and effort responses rather than the effects regarding the decision to apply to a flagship university.[6]

The application trends and the disproportional pool of candidates by high school status reveal that many students from public high schools still do not apply for flagship universities despite the recent inclusive efforts. In this framework, we ask about a specific factor that could influence the decision to pursue a post-secondary education: (1) Do successful applicants act as role models to younger students in the application decision? (2) Does the role model effect differ depending on what kind of high school a student attends? (3) If so, what mechanisms could drive those differences?

2.2 UNICAMP's Admission System

Every year, students interested in attending UNICAMP must take an admission exam composed of Phase 1 and Phase 2 tests. The format varied through the period, but the most important feature is that, upon registry, candidates rank up to three majors. Until 2003, applicants should order the majors within groups (which typically consist of just one major taught in different periods), and since 2004, majors could be ranked freely.

The final grade in the exam is composed of Phase 1 and Phase 2 exams and might include an Aptitude Test for some majors (e.g. Architecture & Urban Studies and Music) or ENEM grades if candidates give permission. The exams were identical for all applicants independently of the majors chosen and covered all high school compulsory disciplines. However, each major has predefined priority disciplines, which

[4]Figure 1 and 2 refer to the period we consider throughout the paper (1990-2018), and do not consider other admission methods adopted by UNICAMP from 2019 onwards.

[5]We will explain in more detail what the AA is in the next section.

[6]Still, some papers address application patterns as mechanisms of the admission effects. Mello (2022), for example, shows that the introduction of the centralized admission system and a nationwide AA policy in Brazil changed the application decision differently among students from different backgrounds.

could be weighted more heavily in the final standardized grade. Thus, there is one final standardized grade for each major choice made by the applicant.

Candidates are accepted according to their final standardized grades and on the availability of slots in each major, respecting their preference rank and the minimum grades associated with the priority disciplines. In general terms, the slots by major are filled based on the following summarized procedure: (a) candidates are ranked in decreasing order of final standardized grades, then (b) are admitted until all slots are attributed to candidates who chose the major as their first choice and obtained the minimum grade required in the priority disciplines. If there are still slots available, then (c) applicants who opted for the major as their second or third choice, and obtained the minimum grade in the priority disciplines are admitted if they have not been admitted to their first option.[7] Although applicants may be admitted in their second or third choices, about 90% of approvals at UNICAMP occur in the first major choices.

Since 2005, students who attended high school exclusively in public institutions can opt for the affirmative action policy (PAAIS). UNICAMP was one of the first universities in the country to adopt affirmative action in the admission system.[8] Eligible applicants receive 30 additional points to the final standardized grades. If they declare themselves as black, brown, or native, they receive another 10 points.

3 Data

The first source of data is the UNICAMP's application records, provided by *Comissão Permanente para os Vestibulares* (COMVEST), the university admission office. It includes detailed administrative information on all individuals who registered to take the UNICAMP exam from 1987 to 2022. This dataset contains all the grades for each applicant in Phase 1 of the admission exam and the standardized grades for those who reached Phase 2, ENEM scores, as well as information on whether the applicant was accepted and enrolled (and in which major) and their major choices. For this study, we restrict

[7]The minimum requirement for priority disciplines varied in format during the period. Until 2008, these minimum grades were binding in almost all the steps of the allocation process (except for the cases where the slots were not filled after the description above). From 2009 onwards, those minimum grades were binding only until step (b). For our setup, it does not matter if the minimum requirement for the priority disciplines was more or less binding. However, the fact that *it is* binding partially explains why our RDD is fuzzy and not sharp – as detailed in section 4.

[8]See Estevan et al. (2019a) for more details of other policies in Brazil.

the sample to applicants from 1990 to 2018.[9]

This rich dataset also includes a comprehensive survey not only about a range of socioeconomic characteristics of the candidates – such as age, sex, race, city/state of residence, household status, parents' education, income and occupation, and the high school attended – but also regarding exam preparation – if they took the exam as trainees or took prep courses, if they applied to other universities and so on. The socioeconomic information is self-reported by applicants when they register for the admission exam.

From all the applicants registered for the university exam, we dropped those who were applying as trainees, since they were not eligible for a university spot, and who did not apply to majors requiring aptitude tests, since those majors do not define admission solely on observable final grades – thus, do not have deterministic cutoff grades to consider in the RD strategy.[10] We also drop those applicants who graduated from high school more than three years earlier in a given year.

We collapse our data to the school-year level, recording the total number of applications/admissions and keeping the average of applicants' socioeconomic characteristics within the school from the first year that the school appears in the data. If a school does not appear in a given year, then zero students from that school applied to UNICAMP. Then, we complete the panel including school-year observations with this information for those units that do not have admissions in a given year.

Our second source of data is the *Censo Escolar da Educação Básica* (Brazilian School Census), provided by *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (National Institute of Higher Studies and Research Anísio Teixeira - INEP),[11] which records demographic and socioeconomic characteristics of the schools from elementary to high school educational level. It also has information on educational inputs – such as the number of teachers, classrooms, and enrollments – and infrastructure variables – e.g. if the school has food and sports facilities, teacher and principals' office, computer and science labs, and waste collection. We link the Census information to the UNICAMP database using the school ID for each year.

Besides these two datasets used in the majority of the paper, we include the public

[9]We use this period for two reasons: (1) some schools lacked information before 1990 and (2) the exam's rules were relatively stable until 2018 – as from 2019, there were huge changes in the admission system that could interfere in the applicant's decision.

[10]We keep the applicants who opted for Dentistry as the first major choice because the aptitude test, in this case, is not binding. The empirical strategy is explained in detail in the next section.

[11]INEP is governmental agency of the Brazilian's Ministry of Education and Culture (MEC). More details on https://www.gov.br/inep/pt-br/areas-de-atuacao/pesquisas-estatisticas-e-indicadores/censo-escolar.

database of ENEM (*Exame Nacional do Ensino Médio*) – an independent national high school exam often used as an admission test to other universities in the country – to exploit one of the possible mechanisms of our effects, in Section 7. This database provides information about grades and participation in the test, which we collapse to the school level and link to our main data by school ID from 2007 onwards.

For additional exercises not related to the effects of older peers' admission on subsequent *applications*, but rather on subsequent *admissions* to the other flagship universities in the state, we use the admission records at the student-level from USP (1999-2018) and UNESP (2000-2003), which provide information only on applicants *who got accepted* to these universities for a brief period. For the analysis considering other longer-term effects of 'peer models' – namely, dropout and graduation in UNICAMP – we include data provided by UNICAMP's Academic Office, which tracks the evolution and performance of those enrolled at the university. These three datasets are linked to the UNICAMP application records by the individual-anonymized ID for each year before collapsing to the school level, and the estimations using these sources are presented in section 9.

The schools in our main sample – those that have never had an admission of a former student into UNICAMP in the past – have lower socioeconomic status than the average school that appears in the university records. Table 1 reports that, on average, our sample of schools (column 1) have worse infrastructure – fewer teacher's rooms and principals' offices, sciences and computer labs, sports facilities, internet access – and are smaller in terms of enrollments and classrooms than the typical school (column 3). More importantly, their overall Socioeconomic Index, provided by the School Census data, is also lower. This means that the students from the schools in our sample have fewer assets, lower household income, and less educated parents.[12]

4 Empirical Strategy

To evaluate the effects of older peers' admission on subsequent applications and deal with identification threats, we employ a Fuzzy Regression Discontinuity approach. The literature in economics of education that employs the RDD strategy typically defines some cutoff rule at the individual level, depending on the specific features of the university or the centralized admission system. In Brazil, for example, where univer-

[12]The Socioeconomic Index is constructed by INEP. We used the Index provided for the first time by the Ministry of Education, released in 2011 with a 1-7 scale. Technical details of the Index provided by INEP (2011).

sities follow exclusive objective criteria to define admission, the relevant cutoff grade is usually defined as the final grade of the last applicant admitted/enrolled in the candidate's choice of major.[13]

However, unlike the usual RDD setup, we need to define a cutoff at the school level to compare the difference in the number of applications in year $t+1$ relative to applications in year t within schools, around the cutoffs. We start by constructing the cutoff grade that each candidate faces as the final standardized grade of the last applicant admitted in the candidate's first major choice in a given year.

It is important to note that, in our context, even though candidates could have up to three final standardized grades (by major choice), we set the individual's running variable as the difference between the final grade of the candidate associated with his or her *first major choice* and the cutoff grade previously defined.

Then, we take the maximum of the individual running variables among the students from each school in a given year. Taking the maximum guarantees that if the schools are below the cutoff, none of their students are above their first major choice thresholds, and if the schools are above the cutoff, at least one of their students is above the first major choice thresholds.

Through this strategy we identify, among the high schools that have never approved any student to UNICAMP, those with students marginally above and below the admission cutoff grades. In practice, we contrast the outcomes between those schools with the first-ever admission to UNICAMP and those schools that remained without any admissions.[14] The following equation estimates a local "intent-to-treat" effect:

$$Y_{i,t+1} = \gamma_0 + \alpha \mathbb{1}(x_{i,t} \geq 0) + \gamma_1 f(x_{i,t}) + \gamma_2 f(x_{i,t}) * \mathbb{1}(x_{i,t} \geq 0) + \eta_t + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t+1}$ is the number of applications of school i in the next year relative to year t, $\mathbb{1}(x_{i,t} \geq 0)$ is an indicator variable equal to 1 if the running variable $x_{i,t}$ exceeds the cutoff grade (rescaled to 0), $f(x_{i,t})$ is a polynomial function of the running variable, and $f(x_{i,t}) * \mathbb{1}(x_{i,t} \geq 0)$ is the interaction term between the polynomial function and the indicator variable, to allow for flexible polynomials above and below the cutoff.

[13] See, for example, Duryea et al. (2023); Francis-Tan and Tannuri-Pianto (2018); Leite (2018).

[14] Our running variable allows schools above the cutoff to have more than one admission to UNICAMP for the first time. However, less than 10% of our main sample have it.

η_t is the year fixed effects, and $\varepsilon_{i,t}$ is the error term clustered at the school level. All regressions control for the baseline number of inscriptions in t.

To recover the local average treatment effect (LATE) of having the first admission to UNICAMP, we must divide the intent-to-treat effect by the admission discontinuity at the cutoff (the first-stage estimate). Then, the fuzzy design recovers the effect of interest for those schools that had a new admission by being above the cutoff grade, at the margin. We estimate the regressions semi-parametrically, using a local linear (or quadratic) polynomial approach with a triangular kernel, analogously to the setup of Calonico et al. (2014). The bandwidths are chosen as proposed by Calonico et al. (2020).[15]

It is important to highlight the interpretation of the effects of a new admission to UNICAMP on subsequent applications. In the main regressions, we are testing if the admission in t of students who graduated (in the last three years) from high schools without any prior admission to the university encourages the application of students who will be graduating from the same high schools in $t + 1$ – i.e. the next immediate high school cohort.

5 Validity of RDD

5.1 McCrary and Balancing Tests

The RDD identification hypothesis states that the units barely below the cutoffs form an adequate counterfactual group to those barely above them. Typically, there are two ways to assess the assumption in our setup. The schools that have never had a student admitted to UNICAMP must (1) not be able to manipulate the running variable – the final standardized grade of their students – to increase the probability of admission, and (2) should not differ in observable (and non-observable) characteristics potentially correlated with the outcomes around the cutoffs.

Figure 3 plots the density of all schools as a function of the running variable – the maximum of running variables among the students from each school in a given year. On the left, each point corresponds to a 1-point local average bin; on the right, we conduct a formal density test (McCrary, 2008). We do the same for the public and private schools in Figures 4 and 5. Not surprisingly, there is no evidence of manipulation of the running variable since no jumps in the number of schools are noticed around the

[15] In RDD setups with multiple cutoffs, the parameter of interest is interpreted as a weighted average of the LATE's across cutoffs (Cattaneo et al., 2016; Bertanha, 2020).

cutoffs (standardized to zero). As UNICAMP is one of the most competitive universities in the country, there is no reason to believe that schools could have any means to interfere with their students' grades discontinuously at the cutoffs.

Figures 6 and 7 show the balancing tests for the variables at the school level that may be relevant to determine our outcome of interest, both considering the whole sample and by high school status (public or private), respectively. These figures illustrate the local linear specification and take year fixed-effects into account, around 50 points from the school cutoffs. Those variables are related to infrastructure – such as the availability of teacher's room, science lab, kitchen, and internet – and other characteristics – if it is located in Sao Paulo State, the number of teachers, if the school is small (less than 200 enrollments) and the number of UNICAMP applications.

Tables 2, 3 and 4 provide the balancing tests considering the optimal bandwidths, and include other relevant variables – availability of office for principals, computer lab, sports court, waste collection, if it is located in an urban area, the number of enrollments and high school classrooms. Except for the number of applications to UNICAMP – which comes from the university application records – all the variables reported in the balancing tests are available in the School Census at the school level. The tables report that there are no significant jumps in any of those variables, neither aggregating the schools nor by high school status.[16]

5.2 Fuzzy Discontinuity

In this subsection, we move to the discontinuities around the cutoffs. Figure 8 illustrates the discontinuity in the probability of admission as a function of the school running variable, pooling cutoffs and years for all schools in the sample and by high school status, considering a 1-point bin average, around the 50-point window. Considering all high schools, there is a sizable discontinuity of 42 percentage points in admission. The discontinuities do not substantially vary across school status: for public schools only, on the bottom left panel of Figure 8, the discontinuity is around 40 percentage points, and for private schools, on the bottom right, it is around 42 per-

[16]Table A.3 shows the balancing tests in terms of students' characteristics from the UNICAMP applicant survey, aggregated at the school level and summarized in three indexes. The first one, the Family Vulnerability Index (FV Index), is constructed using four variables: household income, education of parents, occupation of parents, and internet access at home. The second is the Individual Vulnerability Index (IV Index), constructed using five variables: gender, the status of secondary education (before high school), the period of the day enrolled in high school, and high school regularity. The third one aggregates all the variables in the previous indexes (Vulnerability Index). We use the same weight for each variable.

centage points.

Note that the discontinuities are not sharp. We remind that before constructing the school running variable, we consider the final grade of the last applicant admitted in the candidate's *first major choice* (in a given year). Hence, the school admission shares below the cutoff are not zero because individuals who were not admitted to the first major choice can be admitted to their second or third major choices.

In addition, the school admission rate above the cutoff is not one because the admission is not based solely on the final standardized grade, but also on the minimum grades in the priority disciplines by major, as explained in Section 2.2. I.e., some candidates could have performed well enough to be above the cutoff in the general test but did not get sufficient grades in the most important disciplines of the first major choice, not getting accepted.[17]

Since the magnitude of discontinuities in admission probability might vary across different bandwidths, specifications, and samples considered, we provide the first-stage F-stat in all results tables.

6 Results

6.1 Effects on applications to UNICAMP

After establishing the internal validity of the RDD approach, we illustrate the reduced-form effects in Figure 9 with a local linear fit and report our main results in Table 5. This table reports the LATE of older peers' admission to UNICAMP on t+1 applications at the school level, estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel.

In the first two columns, we show the effects considering all high schools in our sample. The coefficients are statistically significant at 1 and 5% levels, ranging between 0.44-0.52 more applications the following year. It implies that the next immediate cohort from the high schools that had their first student barely admitted to UNICAMP applies more to the university, compared to similar schools just below the cutoff that remained without any students admitted to UNICAMP.

In columns 3-6, we show that the effects are driven mainly by private high schools.

[17] For this to happen, it is sufficient that one of the following occurs: (1) the candidate does not get the minimum grade required in the priority disciplines, despite being above the general grade cutoff, or (2) for a major with n slots, n other candidates with the same first major choice met the minimum criterion for the priority disciplines *and* got a higher grade in the general test.

The coefficients for these schools are statistically significant at 5% level, and punctually higher than for the public ones (0.46-0.61 vs. 0.10-0.35, respectively).[18]

Still, what do these magnitudes mean? Table 6 reports the average in applications for schools at the RDD margin, considering six samples, each of them being a combination of one Panel and one column. For now, we shall focus on the first column, which corresponds to our main sample – the high schools without any prior admissions to UNICAMP. In Panel A, we see that the average of applications in t considering all schools in our sample is 1.40. The average for the public high schools is 1.07 (Panel B) and 1.53 for the private ones (Panel C).[19]

Considering the magnitude of the estimates, it implies that the effect is about 31 to 37% of the baseline applications considering all schools. For public high schools, the effect ranges between 10-32% of the baseline, whereas equivalent to 30-40% for private high schools. In other words, if we suppose that each new admission would contribute the same amount to the application encouragement of the younger students, it would mean that for each three newly admitted students at UNICAMP in a given year, one younger student from the $t+1$ cohort in the same school would be applying the following year.[20]

6.2 Effects on applications to other universities

Until now, we discussed the role model effects on subsequent applications only to UNICAMP. However, the admission of an older high school peer to an elite university can signal to younger students not just the possibility of getting future acceptance at this university, but rather generate a sense that the admission to *other* universities (similar flagship ones or not) is also achievable.

[18]Although we cannot reject that the coefficients for public and private schools are equal (especially in the local linear approach), there is a considerable discrepancy in the patterns of the effects considering even younger cohorts. Despite being less precise, we show in Table A.10 not only that the effects are positive for those students who graduate in t+2 and t+3 in private high schools, but it also increases in time, while the coefficients for the public schools' sample stay around the same magnitude or even smaller, without any statistical significance. We discuss this and other results that support those differences in Sections 7 and 8.

[19]It is not surprising that private high schools have more applicants. Typically in Brazil, private schools are better than public ones. They are smaller, have more privileged students and better socioeconomic status, and perform better in national and university exams. We report some statistics for our sample in Descriptive Tables A.1 and A.2, with particular attention to the last row, where we show the Socioeconomic Index provided by INEP.

[20]Unfortunately, we cannot test this assumption because more than 90% of the schools in the sample have just one admission for the first time. In a related but different exercise (omitted), we test if the second admission – given only one admission in the past – plays any role. There is no evidence that it does.

On the one hand, if this new signaling corresponds uniquely to the feasibility of a UNICAMP admission, then we would expect that applications only to UNICAMP increase. On the other hand, if it represents that a post-secondary path is possible in a broader way, we should expect that applications to other universities increase as well.

We investigate this by estimating the RD regressions using a specific question from UNICAMP's survey, which asks the applicants what other universities they would apply to besides UNICAMP. There were seven alternatives that applicants could choose to answer this question: the first one is "Only UNICAMP"; three of them are related to the other flagship universities in Sao Paulo State – "UNICAMP and USP", "UNICAMP and UNESP", "UNICAMP, USP and UNESP" – and the last three related to broader categories – "UNICAMP and other private universities", "UNICAMP and other public universities", "UNICAMP and other public and private universities". Unfortunately, this question was asked only in four years of our sample (2000-2003). We take the results as suggestive evidence.

In Figure 10 we illustrate the reduced-form estimations for each alternative separately. Considering all the high schools, we see that the previous peer admission to UNICAMP does not encourage the following cohort to apply for the *specific* set of the other two flagship universities in the state (USP and UNESP), but does encourage the application to the broader categories of "UNICAMP and other public universities" and "UNICAMP and other public and private universities", as shown by the jumps at the cutoff for these variables. We report the LATE's magnitudes related to those jumps in Table 7 – 0.32 and 0.23, statistically significant at 1% and 5% levels, respectively.

In Tables 8 and 9 we run the same exercise by high school status. The results suggest that private high schools drive the overall results, with sizable effects in the same categories ("UNICAMP/other public universities" and "UNICAMP/other public and private universities") – magnitudes 0.29 and 0.23. For the public high schools, we see a positive (but not statistically significant) coefficient for "Only UNICAMP" and a more precise yet small coefficient for "UNICAMP/other public universities", consistent with the fact that we did not find strong evidence of the effects for the public high schools earlier.

This suggestive evidence, particularly for private schools, does not mean that students do not apply more to the major UNICAMP competitors. USP and UNESP are also public universities: applicants could still be applying more to one of these institutions (or both) as a result of the previous peer admission to UNICAMP. But if so, they do that along with other public alternatives, in the broader set of public universities –

which contains USP and UNESP and certainly other unspecified universities.[21] [22]

7 Mechanisms

In this section, we examine some mechanisms behind the effects reported thus far. Specifically, we try to understand why the younger cohorts from private high schools, but not from public high schools, are encouraged to apply to UNICAMP after the school's first-ever admission to the university.

7.1 Role model information

One possible explanation for the differences we observe in the encouragement effect is related to how 'visible' the role model is to the eyes of the younger students. To be perceived as such, first, the information about his accomplishments needs by any means to reach those who could be influenced, either by facilitating conditions of the environment or by active dissemination – for instance, by the schools themselves.

We try to assess the informational mechanisms in three different heterogeneity exercises. Firstly, we separate the samples between two periods, before and after the introduction of an AA policy at UNICAMP. Some papers discuss that the AA itself can change the overall level of admission information when it shifts the slots towards the targeted students – the public high school students in our context (Holzer and Neumark, 2006; Page and Scott-Clayton, 2016). This, in turn, could alter the relevance of the information provided by the first school's admission differently according to high school status.

Secondly, we estimate heterogeneous effects by school size (above and below the median number of high school enrollments). On the one hand, bigger schools could help the information of the first admissions to travel faster and reach more students.

[21] Tables A.4, A.5 and A.6 report the coefficients for the local quadratic polynomial. The results are similar.

[22] Another way to test (at least suggestively) whether an older peer's admission results in application to other public universities is to run our main regression using ENEM inscriptions in the following years, as the grades in this exam are frequently used as a way to get into these institutions. With the caveat that the ENEM database can only be linked to schools from 2007 onwards (thus reducing statistical power), the analysis shows big, positive yet imprecise coefficients for the public high school sample (around 10-30 inscriptions) as a result of a previous peer admission to UNICAMP, whereas small, negative and insignificant coefficients for private students (-2 inscriptions). These estimates do not work against our results because there is not much space for an increase for the latter group: in general, the ENEM participation rate is already high in private schools (more than 90%), while low (60%) in public schools (LaPOpE-UFRJ and NIED-UFRJ, 2023). Results are provided upon request.

But on the other hand, one or two new admissions among bigger pools of students could reduce the salience of the information.

Thirdly, we examine if the school location plays a role in our context. The information may be more impactful the closer the schools are to the university – for example, through a higher probability of knowing UNICAMP or valuing the acceptance at the university. In particular, we investigate if our effects systematically differ between schools from Sao Paulo State, where the university is located, and schools from outside the State.[23]

Figure 11 and the first two columns of Table 10 report the heterogeneity effects considering all schools in our sample. The estimates show that the general effects of a new admission to UNICAMP are concentrated in the absence of the AA (significant at 1%), somewhat in schools bigger than the median number of enrollments (significant at 10%), and schools located in Sao Paulo State (significant at 5%).

However, we could not rule out that the coefficients are equal. Figure 12 and the rest of the columns of Table 10 depict the results by high school status. Although we could only reject the null of zero effects in the absence of AA[24] and for SP State's location for the private high school sample, the results are noisy and we cannot distinguish these informational channels.

Unfortunately, we cannot observe whether, within the schools, teachers and principals take more straightforward actions related to the sharing of alumni achievements. Given that the admissions to the State flagship universities occur after the end of the school year (and usually during the school holidays), the schools would need to make an active effort to disseminate this information to the younger cohorts – for instance, intentionally advertising former students' admission in internal communications, or bringing the successful cases to classrooms and talks to raise awareness about alternatives after high school.

[23] Griffith and Rothstein (2009) documented that, in general, students are more likely to apply for closer selective colleges, either because of reduced cost of traveling, more convenience to enjoy what the institutions have to offer, or even because "(...) living close to a college may raise awareness of opportunities available at post-secondary institutions and help create a college-going expectation for nearby youths. (...)" (pg.2). However, it is unknown if the role model effect itself varies according to geographic distance.

[24] If the AA policies themselves directly provide sufficient information about the admission probability, the school's first admission to UNICAMP could not disclose any additional information to the younger cohorts since its introduction. Indeed, Estevan et al. (2019a) reports that the UNICAMP's affirmative action caused a redistribution of admissions towards applicants from public high schools. However, we could not draw any further conclusions due to the imprecision of the AA heterogeneity estimates. Then, the question of whether the overall level of information or the groups' specific admission perceptions would mediate the role model effects remains open to further research.

Still, it is worth noting that between public and private schools, only the latter have economic incentives to attract students – these schools not only charge tuition but also have the autonomy to select students following any criteria, for example, to attract the higher-performing ones. Thus, it is reasonable to assume that private schools would be more willing to use advertising devices to stimulate younger students to emulate the successful ones or as a way to build the reputation of a good school.

We provide anecdotal evidence that this could be the case. In a selected sample, we see that both types of schools inform important admission exam dates (for ENEM and the state public universities, for instance) in their social media. However, the public schools of this particular sample used these tools much more to inform about the state and national evaluations and programs, the school calendar, and commemorative dates in the last three years, and only a few expressly published a post about their students' higher education approvals.[25] For the selected private schools, on the contrary, the admissions were a typical post – almost all of them did it.[26]

7.2 Role model proximity

Another possible explanation is related to the role model proximity. The 'closer' the younger cohort is to the peers admitted to the university, the more likely the students are to have shared the same school environment. In addition, they are more likely to have known each other and have developed stronger social links in high school. Thus, the admission of an older peer would become more salient, and more prone would be the younger ones to consider the post-secondary path (Altmejd et al., 2021; Allende-Labbé et al., 2023; Barrios-Fernández, 2022).

We examine the role model proximity mechanism in two ways. First, we restrict the potential 'influencers' to be those admitted to the university directly from the high school, instead of having graduated in the last three years. In this scenario, the potential 'influencers' are exactly one school year ahead of the next cohort.

Figure 13 illustrates the reduced-form effect considering the closer 'influencers' alongside the graph for the main result using the same scale. Together with the first two columns of Table 11, we see that the magnitudes are pointwise higher: while the main overall effects on the applications from the t+1 cohort was around 0.44-0.52 (in

[25] Examples of evaluations are SARESP, Provão Paulista, SAEB.

[26] We selected 28 public and private schools (fourteen of each) in different parts of the distribution of Figure 14 (from -20 to +60 in terms of the constructed distance) to explore their recent social media activity in Facebook and Instagram. Examples of typical posts and the posts with the approvals are given in Figures A.7 and A.8.

Table 5), the LATE considering the 'closer models' increases to 0.77-0.83 applications.

As before, we note that the effects in terms of school calendar proximity are driven by the private schools. While the coefficients for private schools (columns 5-6) increase to 0.63-0.88 applications, the coefficients for public schools (columns 3-4) remain small and insignificant. Combined with the main results, these estimates suggest that not only the private high school youngsters respond differently from public high school ones in general, but also that 'closeness' – as we first defined it – matters distinctively across groups.

But why are younger students from public high schools not affected at all? One hypothesis relies on the context of Brazilian schools and another behavioral pattern. It is possible that, differently from the private school students, the public school students who are admitted at a flagship university are so distant from their peers in terms of university exam preparedness or ability, for example, that they do not appear as role models to the younger ones. In other words, the younger students who could be (but are not) influenced might not see themselves pursuing the same path as those who were admitted, because the successful applicants are 'so much better'.

We suggestively test this hypothesis with our second measure of proximity, which considers the distribution of test scores in ENEM, an independent high school exam also used to complement the UNICAMP's final score, and recently, as an admission test to other public universities.[27] We link the ENEM information to our main dataset using the ENEM grades, which are also available in the UNICAMP database. From the ENEM database, we record the grade percentiles of all the participants according to the distribution of the State of Sao Paulo. Then, having the school ID in both datasets we calculate the distances between the ENEM grade of the students at the university margin and the grade of the other ENEM participants in the same school.

Figure 14 plots the empirical CDF of the average and median distance by schools in terms of percentiles of ENEM test scores, between the student admitted at the margin of UNICAMP and the rest of the students from the same school.[28] We note that the students' distance from their potential 'influencer' is much bigger for public high schools than for private high schools, which would be consistent with the differential behavioral responses by school status.

[27] The 'other public universities' are mainly the federal ones. Since 2000, if the applicant has taken ENEM and given permission to the State universities, the grade of Phase 1 could contain a percentage of the ENEM grade. But in the period considered in this paper, the ENEM was not an admission test either to UNICAMP or to USP and UNESP.

[28] The ENEM database can only be linked to schools from 2007 onwards. In this exercise, we use only participants from 2007 and 2008.

On top of that, if it is true that the 'ability' proximity of role models plays a role in determining the behavioral response of younger students, we could test if there is any difference in future application effects considering the competitiveness of the majors that the older peers are admitted to. In our framework, the competitiveness of a major is closely tied to the grade cutoffs at the individual level – i.e., the higher the standardized grade of the last applicant admitted, the greater the difficulty of getting accepted to this major.[29]

To get another piece of evidence, we ran our main RD specification splitting the original samples into below and above the majors' median rank of cutoffs (below and above median competitiveness). In Table 12 we report the results: the public high school students react by applying more in t+1 only when the older peer is admitted to the less competitive majors (+0.90 to 0.95 applications), whereas the private high school students react disproportionately when the older peer is admitted to the more competitive majors (around +0.5 applications).

Putting together, the last two exercises suggest that, beyond inspiring by their achievements, role models must represent realistic possibilities – at least in this specific context. Although we could not perfectly assess and rule out the information mechanism earlier, this subsection indicates an alternative explanation for the differences in the role model effects, which should be deepened in future research.

8 Robustness Checks

We run a series of robustness analyses to check if our effects persist in different specifications and to rule out some alternative interpretations. In Figure A.1 we show that the effect of a new admission of an older high school peer remains similar when we use alternative bandwidths in the local linear and quadratic specifications and when we control for student characteristics. Figures A.2 and A.3 report the same exercises by high school status. We also provide balancing tests for all the different samples regarding the analysis of the possible mechanisms in Tables A.7-A.9.[30]

Still, one may be concerned if our effects are just capturing a shift of the application

[29] Delaney and Devereux (2020) show that among students with similar chances of college admission, those from advantaged high schools are more likely to apply for universities and more selective college programs. However, we do not know if having older peers applying to more or less selective programs contributes to this pattern, i.e., if it induces any different application responses by high school status.

[30] In these tables, we already tried to diminish the dimension of the tests combining the school and student characteristics in three different indexes of vulnerability, using the variables that we already tested for balancing in Section 5, to mitigate the multiple hypothesis problem.

pattern of the younger cohort, and not exactly adding the post-secondary education option as a prospect. In other words, it is possible that, even in the absence of the school's first admission to UNICAMP, students from the younger cohort would apply anyway to other universities in t+1 – then, our coefficients would represent just a rearrangement in the set of applications. In Figure A.4 we show that the effects are mainly driven by those students that answered "none" when asked "How many application exams have you done *before*?".[31]

Another concern is whether the effects we report might be capturing just an upward trend in applications. If this were the case, we would not expect to see any discontinuities in the main outcomes, since schools above and below the cutoffs would be increasing their applications over the years. In addition, we see in Table 6 that the schools' average number of applications in our sample is declining. So, if anything, a barely new admission to UNICAMP mitigates the declining trend of subsequent applications to the same university.

Finally, one may also wonder if our results for the sample of schools that have never experienced any prior admission to UNICAMP is just a particular case of a broader phenomenon and, therefore not related by any means to the salience of a new fact. In this scenario, we would note sizable effects on schools without any particular sample restriction. In Figure A.5 we show that no effects are detected when we consider all the schools that appear in the university administrative data, i.e., regardless of past admissions. However, when we look at a sample with a different but milder restriction than ours – of schools that have not experienced any admission to UNICAMP *in the last three years* – the effects are fairly comparable to what we reported throughout the paper (Figure A.6). Although some caveats may apply in this comparison, it is another suggestive evidence that an unprecedented or rare admission elicits future applications.[32]

9 Persistence of the effects and longer-term outcomes

One may wonder if our effects on applications are restricted only to the students who would have the chance to apply in the next immediate year. We test if the older peer admission to UNICAMP in t affects not only the next immediate cohort but also cohorts that graduate from high school in t+2 and t+3 in the first chance they have to

[31]This question was asked to all applicants in the UNICAMP's survey, between 1990-2003.

[32]In these additional exercises, a given school could be on both sides of the cutoff in different years. However, the year fixed-effects and the cluster at the school level should alleviate concerns.

apply for the university (Table A.10).

We must highlight that this exercise presents huge caveats: the schools (with no past admissions to UNICAMP before *t*) on the right of the cutoff may have had other admissions in the additional years until these cohorts could apply. On the left, the schools could have remained without any admissions or not. Hence, we are not recovering the effect of a *new* admission anymore, but the effects of a new admission *two or three years* ago while all sorts of things could have happened meanwhile – probably making the schools at the margin not comparable anymore.[33] With this in mind, we report positive overall effects for cohorts graduating two and three years later, driven by students from private high schools.

We also investigate if the encouragement effect that we have shown translates into university access. In terms of public policy, it is important to understand if, after being nudged to take the admission exam, those additional applications turn into acceptance or a higher education degree later.

Table 13 provides the effects of the older peers admission to UNICAMP on t+1 admissions and enrollments at the same university, and Tables 14 and 15 show the estimates for graduation – between 3 and 6 years after application – and dropout – between 1 and 6 years after application. We also provide, in Table A.12, the estimates for admission to the other two flagship universities in the state, USP and UNESP, for the years that we have data on their admission records.

The results show precise zero effects: we do not find any evidence on those longer-term outcomes. Hence, any encouragement stops at the point of the application decision.

10 Discussion

The idea that one's actions can influence other people's behavior is not new in the economic literature. Akerlof and Kranton (2000, 2002), for instance, conceptualize a framework that shows how people tend to value the choices of their social networks or from people in the same 'social categories'.

In higher education, it is well established that a role model can be manifested through a same-gender and same-race professor (e.g. Borges and Estevan, 2024; Carrell

[33]This same identification problem occurs if we fixed the next immediate cohort and estimated the effect of the older peer admission on this cohort not on t+1 applications but on applications in later years – when they are not in the last year of high school anymore. Still, we also provide these effects in Table A.11. The role model effect for the next immediate cohort does not seem to hold for later applications.

et al., 2010; Fairlie et al., 2014; Hoffmann and Oreopoulos, 2009), improving student performance, influencing subject interests and future careers. Regardless of whether the role model's influence comes either from representativeness or salience, they reveal a possibility (or feasibility) of different achievements or trajectories.

However, recent research also shows that, for students coming from more disadvantaged backgrounds, just providing information about a post-secondary possibility in the first place is not enough to influence their willingness to pursue it. Bettinger et al. (2012) and Barrios-Fernández et al. (2023), for instance, show that only providing information about college aid programs and higher education systems did not increase college applications. However, when the information is packed with personal assistance to fill the aid form or with personalized mentorship, the interventions greatly affected registration and admission exam applications in the United States and Chile. Oreopoulos et al. (2017) and Oreopoulos and Ford (2019) also show large effects of mentoring, daily tutoring and workshop activities on college application and enrollment in Canada.[34]

Therefore, although we cannot perfectly distinguish that the information about role models drives the differences between students from public and private high schools, it is still possible that even in the presence of widespread information, a successful application from a public high school student had limited effects. Our suggestive evidence indicates that for the role model to be effective, not only 'social categories' or social proximity matters, but also the perception that his accomplishments are 'achievable' in the eyes of the younger students.

Nevertheless, the encouraged applications are not successful. I.e., they apply but are not accepted in the end. From a public policy perspective, this is crucial: role models have the potential to nudge students to take the admission exam but they do not help to increase access to these flagship universities.

It is not clear, though, that this could merely reflect the size or the scale of the effects we estimate, or if it means that role models do not affect dimensions related to effort and exam preparation. Even if it affects those dimensions, role models may not be sufficient to make younger students overcome a high-stakes and highly competitive admission test.

Anyway, we still need more empirical research to understand if our suggestive evidence holds in other educational contexts, and to what extent the role models are important. In addition, further research is needed to understand what kind of emotions,

[34]For a more comprehensive analysis of such programs in US or a broader review of Canada, see Carrell and Sacerdote (2017) and Oreopoulos (2021), respectively.

reactions, or responses could be triggered by different characteristics of role models.

11 Conclusion

In this paper, we evaluate if a student's admission to a flagship university increases the number of applications of younger cohorts from the same high schools. Using a fuzzy regression discontinuity approach, our results indicate that a successful application to UNICAMP encourages younger peers to apply to the university and other public universities the following year. Nonetheless, only students from private high schools seem to be affected.

We investigate two possible mechanisms. First, we do a heterogeneity analysis to understand if the information about the role models plays a role. We could only reject the null of zero effects in the absence of AA and for SP State's location for the private high school sample. However, these estimates are noisier, so we cannot perfectly assess if the different incentives to spread the new information between public and private schools contribute to our effects. Yet, as we show anecdotally, the public and private schools behave very distinctively when it comes to post-secondary education and the information about their student's admission to universities.

Additionally, we find that, for private students, the encouragement effects are more pronounced when the older peer is just one school year ahead, suggesting increasing effects when social links are stronger. We also report that relative to private students, public high school students are further away from their potential role models in terms of test scores in an independent national exam. This, in turn, could provide an explanation for why we do not detect general increases in applications for public schools but find positive effects for private ones.

Related to this alternative explanation, we show that public high school students only apply more when their older peers are admitted to the least competitive majors, whereas private high school students apply more when their older peers are admitted to the most competitive ones. Together with the grade distance patterns we observe in the independent exam, these results are consistent with the fact that for a role model to be effective, it should be 'closer' enough socially and in terms of possible achievements.

The main results consider the sample of schools without any prior admissions. We find similar effects when we impose a milder restriction on the sample – schools that did not have an admission in the last three years –, but no effects considering all schools regardless of past admissions. These findings suggest that role models are more important when the admission is unique or rare, and thus more salient to the younger ones.

Importantly, we show that the encouraged applicants do not necessarily get accepted. We do not find any effects on longer-term outcomes, such as admission, enrollment, conclusion, or dropout. Hence, although role models increased the willingness of younger students to apply, they did not increase university access.

To better understand the role model phenomenon in higher education, we still need further research in other contexts. In policy terms, it is crucial to know to what extent the role model is effective and to investigate what kind of behavioral attitudes the role model can trigger in order to inspire younger students. Research in this direction could contribute to design other policies to improve access to higher education.

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Figures and Tables

Figures

Figure 1: UNICAMP application trends

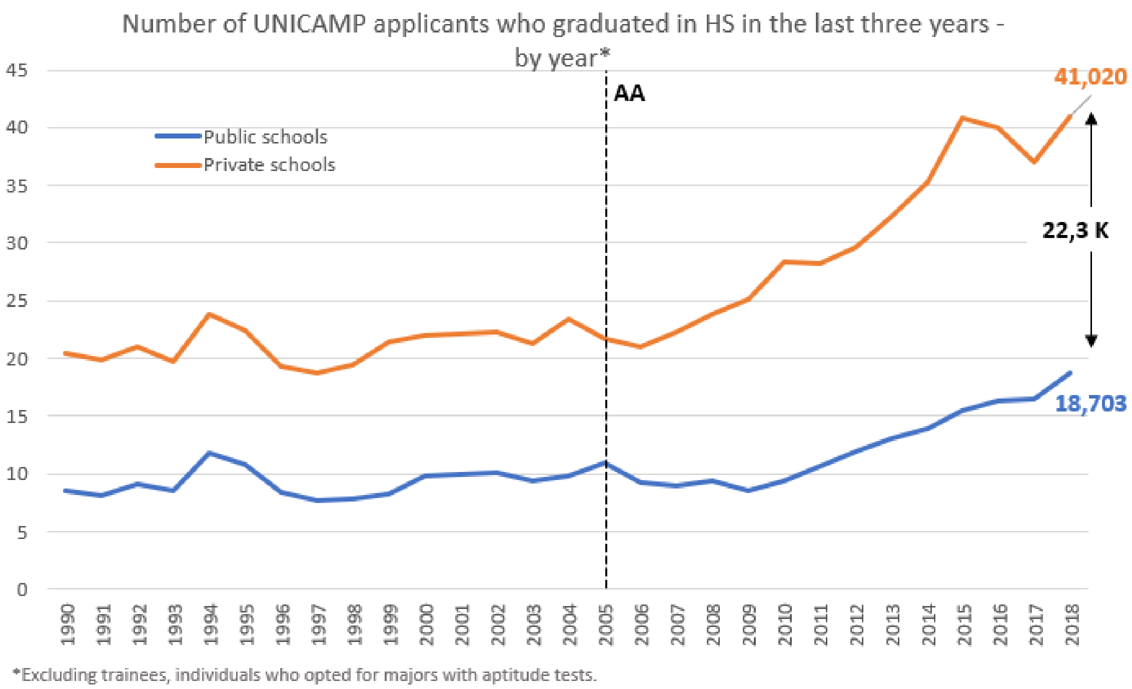


Figure 2: UNICAMP "sending" schools

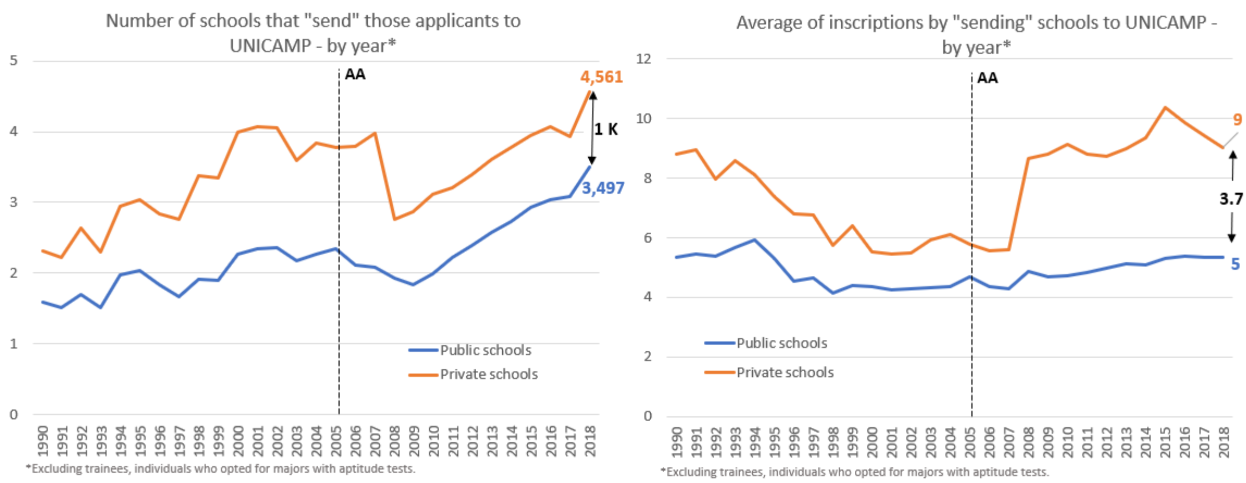
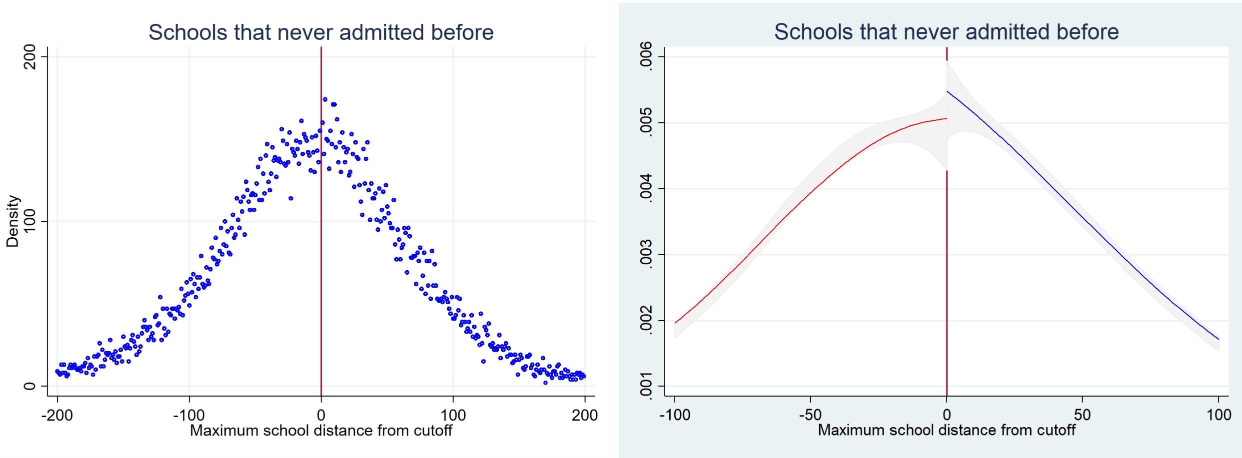
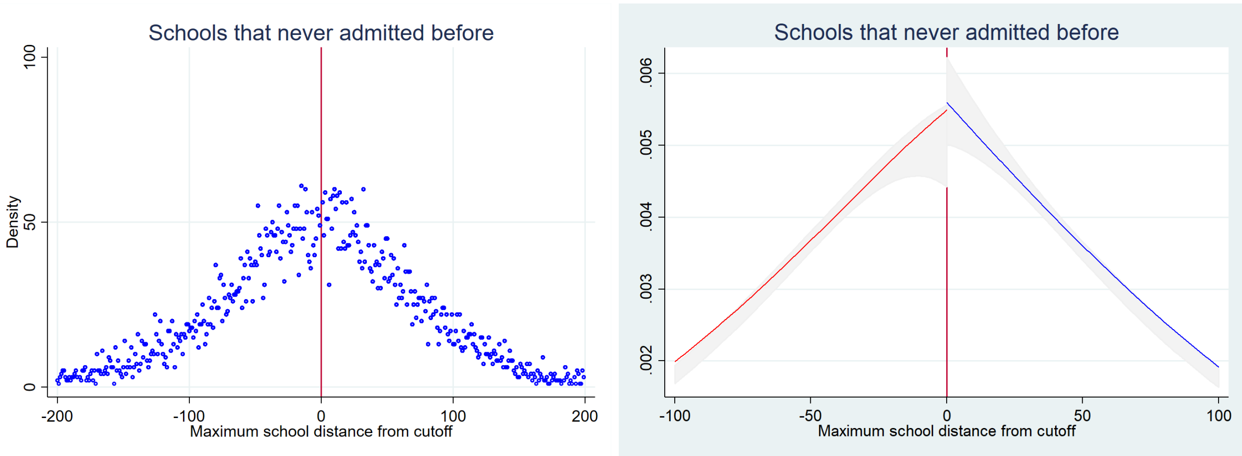


Figure 3: McCrary Test - all high schools



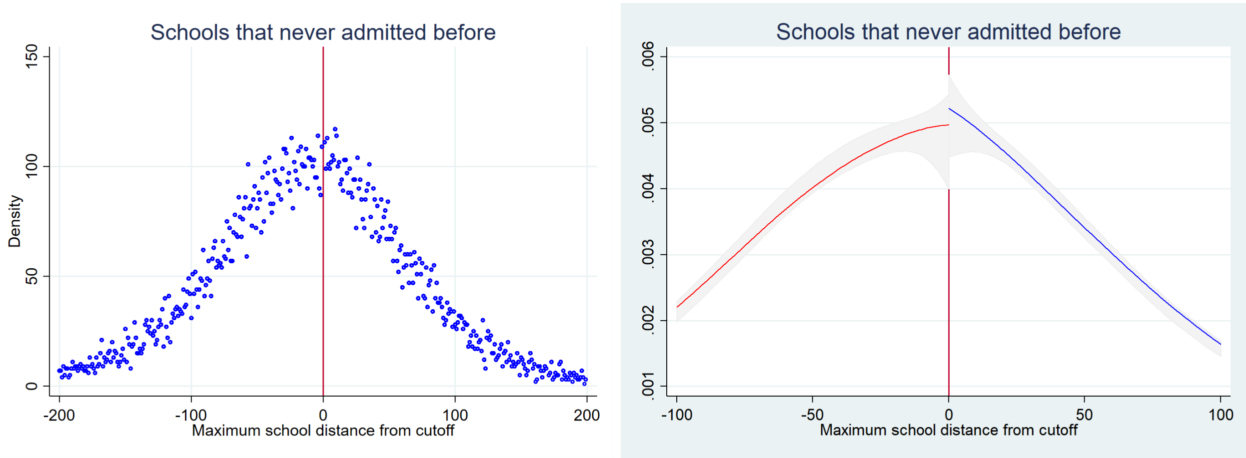
Notes: This figure reports the density of all schools as a function of the running variable. On the left, each blue dot represents a 1-point local average. On the right, it reports the formal density test at the cutoff, standardized to zero.

Figure 4: McCrary Test - public high schools



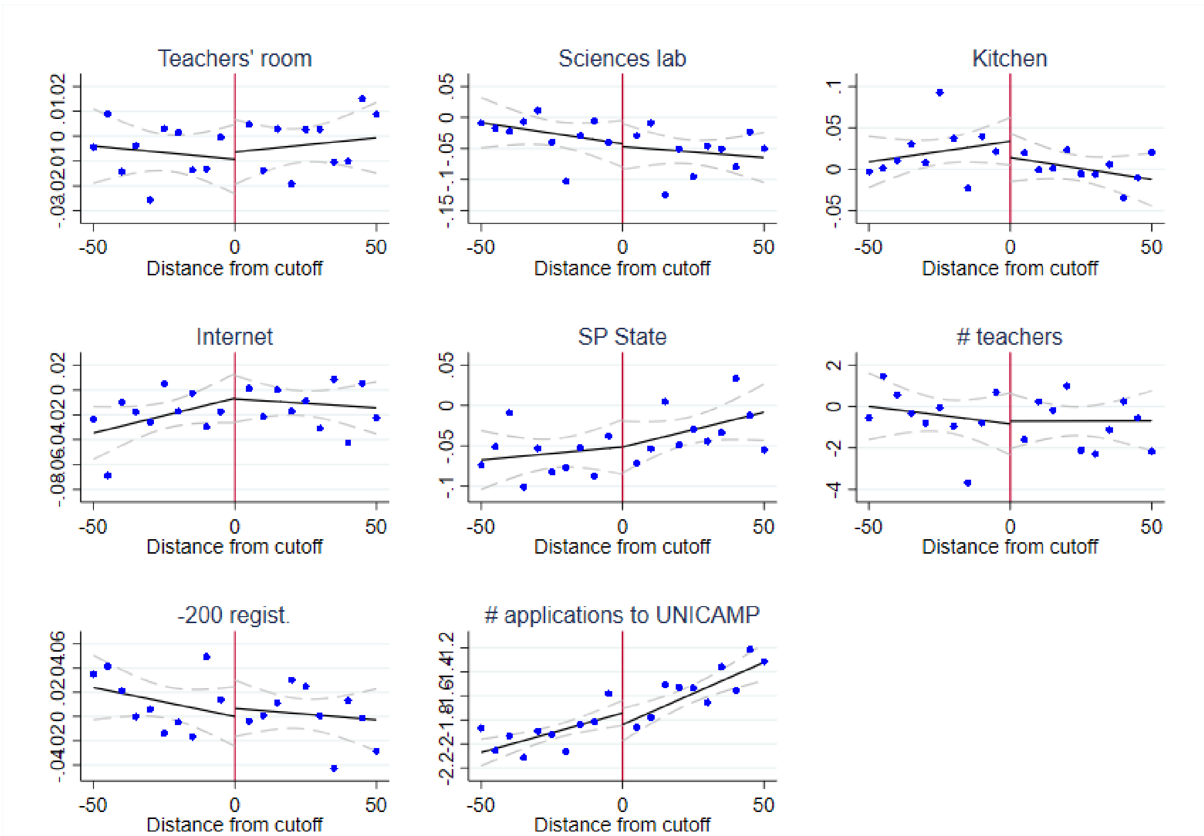
Notes: This figure reports the density of public schools as a function of the running variable. On the left, each blue dot represents a 1-point local average. On the right, it reports the formal density test at the cutoff, standardized to zero.

Figure 5: McCrary Test - private high schools



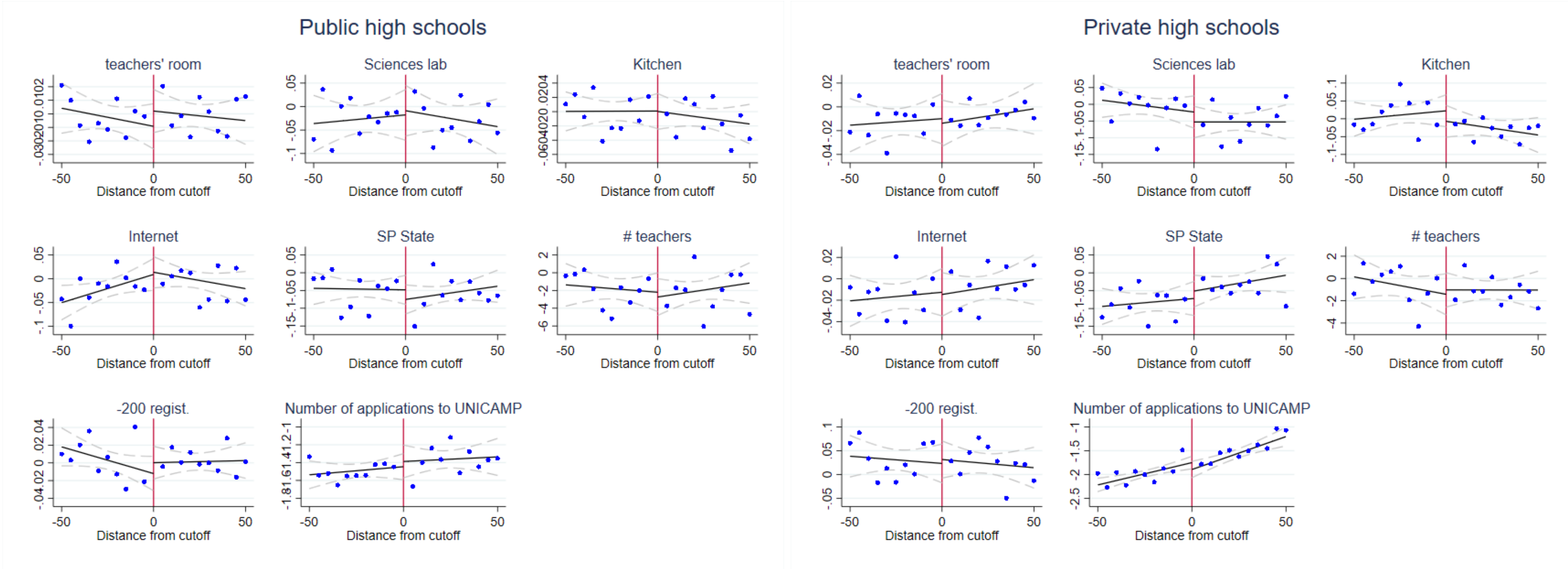
Notes: This figure reports the density of private schools as a function of the running variable. On the left, each blue dot represents a 1-point local average. On the right, it reports the formal density test at the cutoff, standardized to zero.

Figure 6: Balancing Tests - all high schools



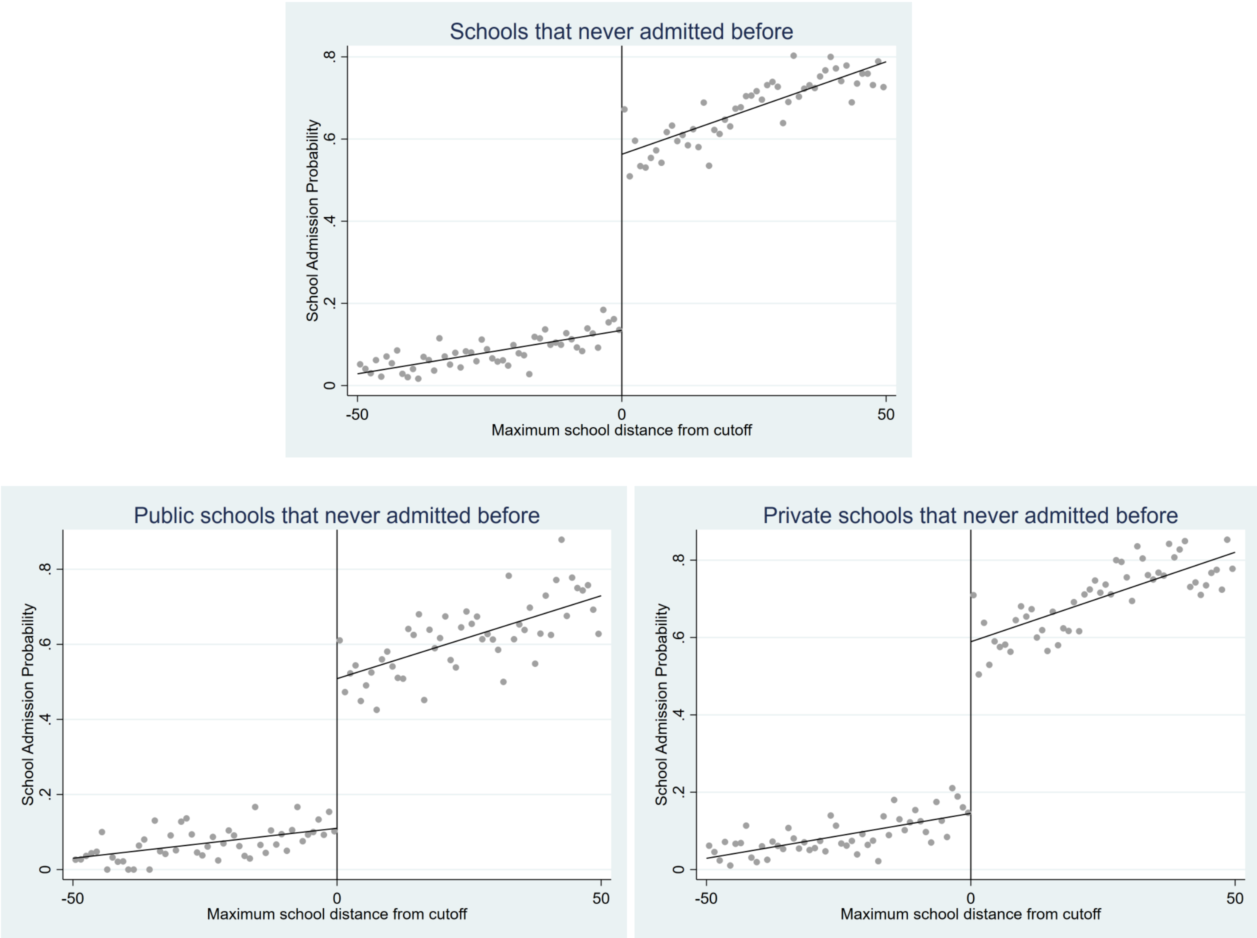
Notes: This figure illustrates the balancing tests for the school characteristics. Except for the number of applications to UNICAMP – which comes from the admission database – all the variables are available in the School Census. The window considered is +- 50 points around the cutoff.

Figure 7: Balancing Tests - by high school status



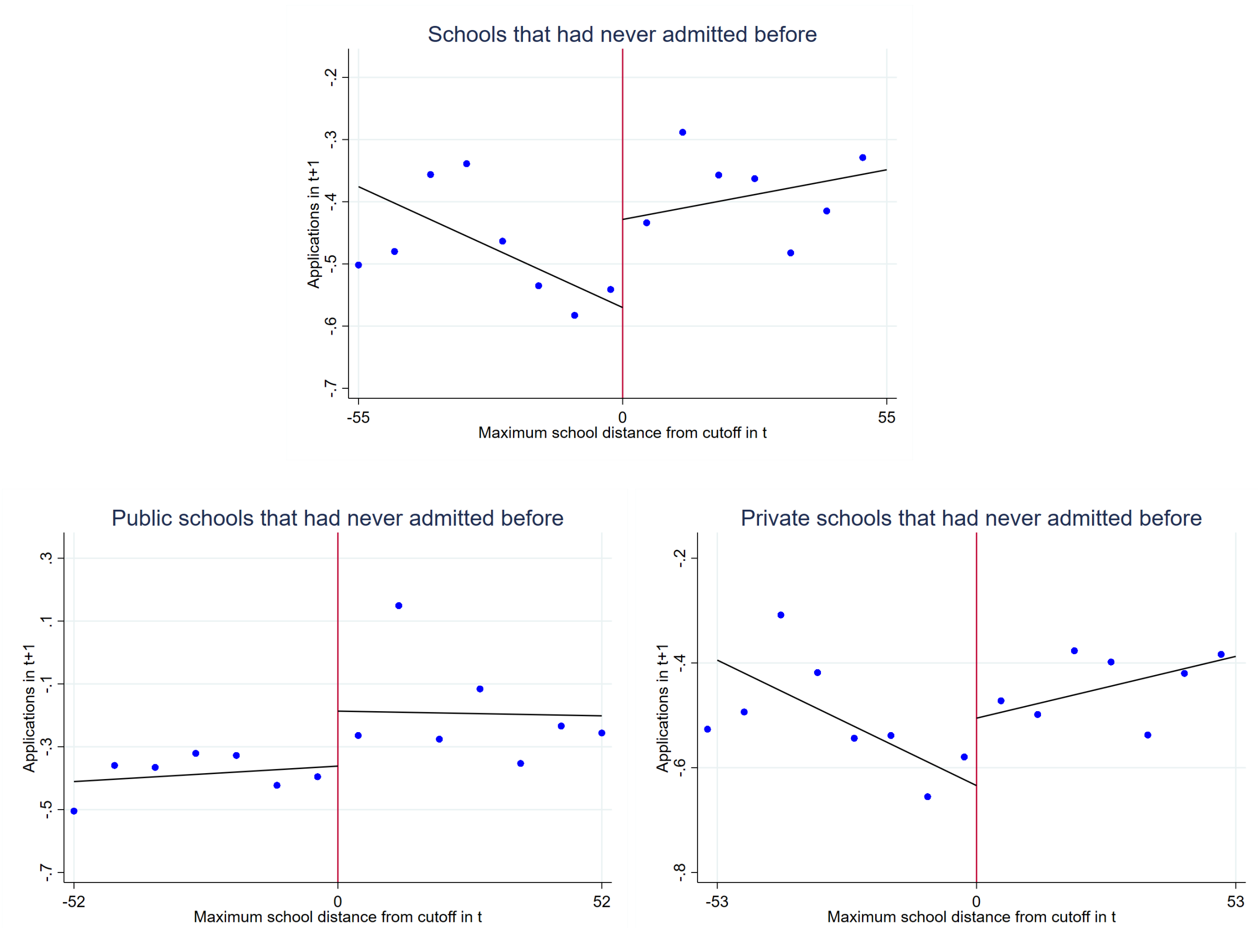
Notes: This figure illustrates the balancing tests for the school characteristics by high school status (public vs. private). Except for the number of applications to UNICAMP – which comes from the admission database – all the variables are available in the School Census. The window considered is +- 50 points around the cutoff.

Figure 8: First Stage



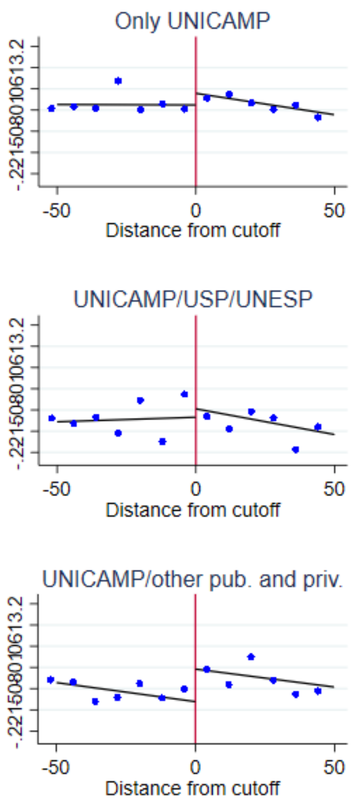
Notes: This figure plots the admission discontinuity probability for all the schools as a function of the school running variable. Each dot represents a 1-point local average. The window considered is +- 50 points around the cutoff. All high schools are considered on the top panel. Public high schools are on the bottom left, and private high schools are on the bottom right.

Figure 9: Reduced-form effects



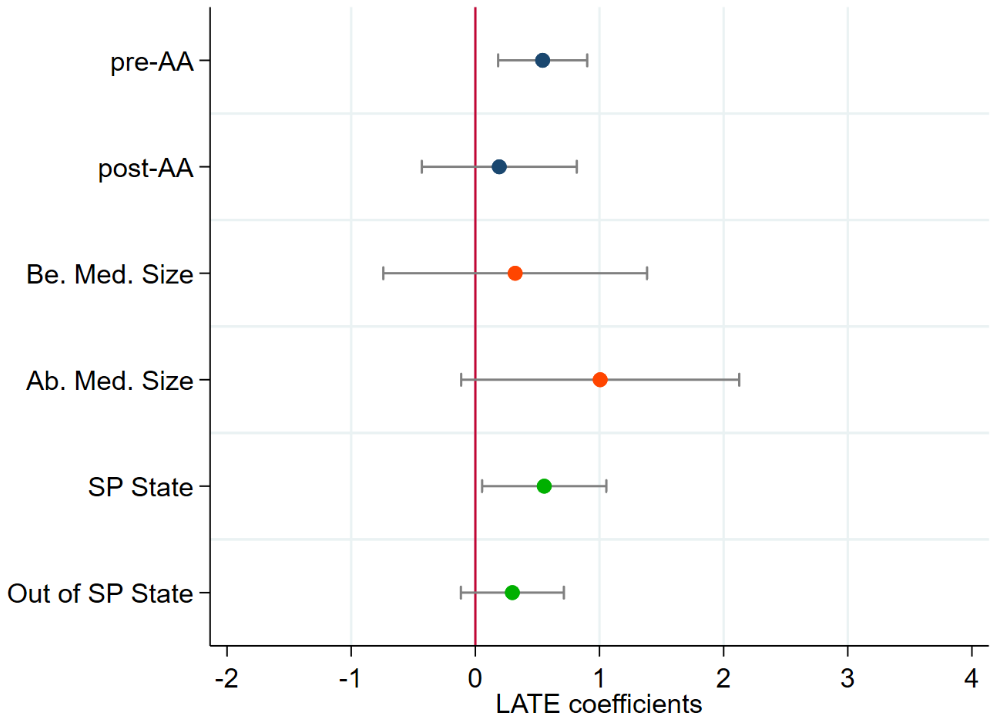
Notes: This figure illustrates the reduced-form effects (ITT) of older peers' admission to UNICAMP on university applications the following year. In the top panel, all high schools are considered. On the bottom left, only public high schools. On the bottom right, only private high schools.

Figure 10: Effects on applications to other universities - all high schools



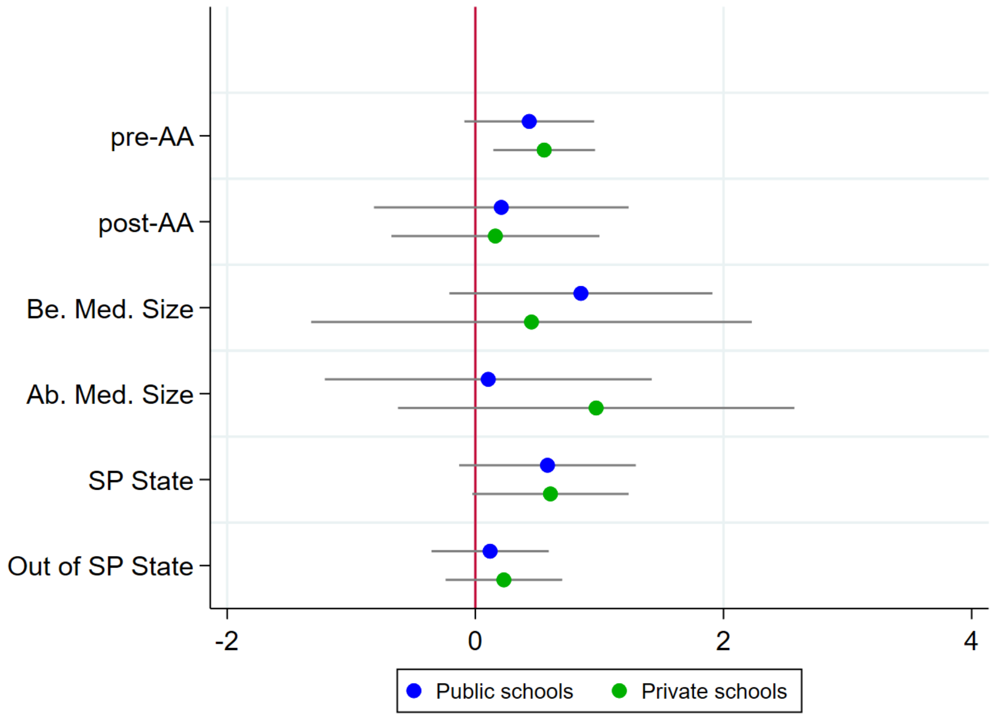
Notes: This figure illustrates the reduced-form effects (ITT) of older peers' admission to UNICAMP on other university applications the following year, considering all schools in the sample.

Figure 11: Informational channels - all high schools



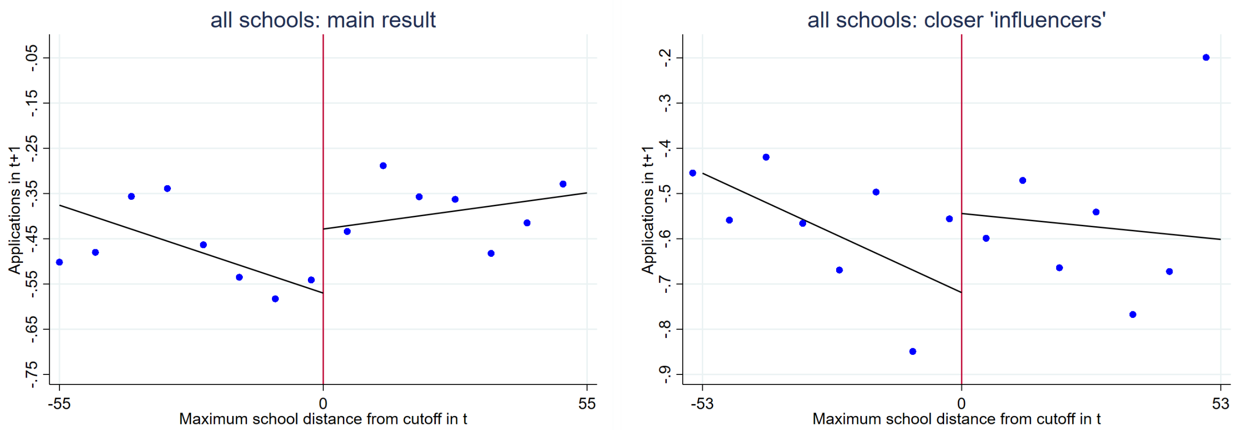
Notes: This figure illustrates the heterogeneous LATE of older peers' admission to UNICAMP on other university applications the following year, considering all schools in the sample.

Figure 12: Informational channels - by high school status



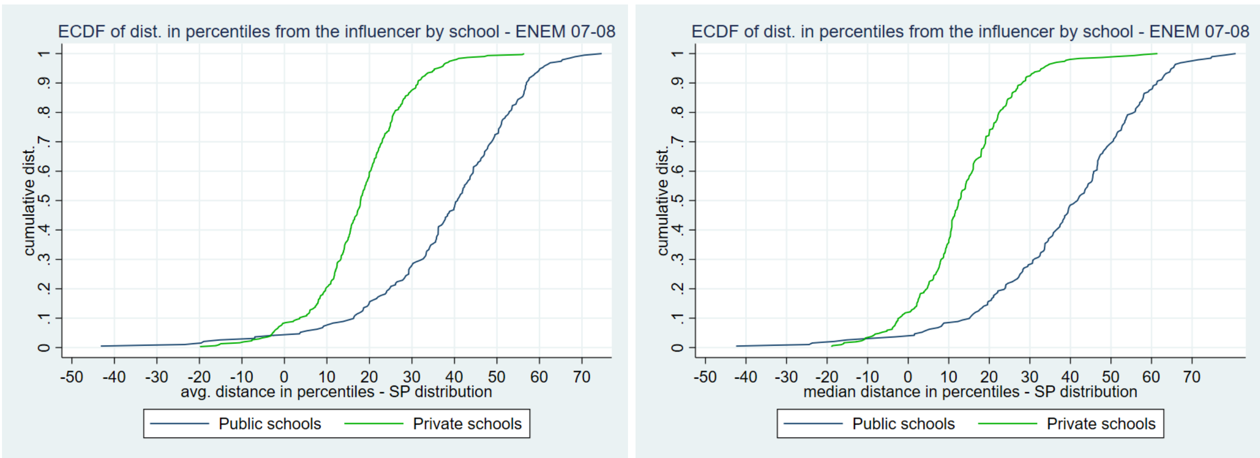
Notes: This figure illustrates the heterogeneous LATE of older peers' admission to UNICAMP on other university applications the following year, by high school status.

Figure 13: Reduced-form effects - main sample vs. closer 'influencers' sample



Notes: This figure illustrates the reduced-form effects (ITT) of older peers' admission to UNICAMP on applications the following year for all schools. On the left, we re-plot the graph for the main sample, and on the right, we plot the graph for the closer 'influencers' sample.

Figure 14: Empirical CDFs of ENEM percentile distance - by high school status



Notes: These figures plot the empirical CDF of the average (left) and median (right) distance by school in terms of percentiles of ENEM grades between the student admitted at the margin of UNICAMP and the rest of the students from the same school. We use the ENEM database from 2007 and 2008. We used the ENEM grade distribution of Sao Paulo state as a reference.

Tables

Table 1: Descriptive Statistics

	0 students adm. (main)	0 students adm. past 3 y.	Regard. of past adm.
Panel A: School Infrastructure			
Teachers' room	0.968	0.971	0.972
	(0.18)	(0.17)	(0.17)
Principal's office	0.928	0.937	0.933
	(0.26)	(0.24)	(0.25)
Sciences lab	0.531	0.548	0.581
	(0.50)	(0.50)	(0.49)
Computer lab	0.845	0.854	0.849
	(0.36)	(0.35)	(0.36)
Kitchen	0.816	0.830	0.813
	(0.39)	(0.38)	(0.39)
Sports court	0.830	0.843	0.841
	(0.38)	(0.36)	(0.37)
Internet	0.920	0.922	0.936
	(0.27)	(0.27)	(0.24)
Waste collection	0.992	0.993	0.992
	(0.09)	(0.08)	(0.09)
Observations	10272	14225	26912
Panel B: School Characteristics			
SP State	0.706	0.709	0.755
	(0.46)	(0.45)	(0.43)
Urban	0.991	0.993	0.994
	(0.10)	(0.08)	(0.07)
Teachers	21.536	22.641	22.714
	(18.52)	(18.94)	(18.95)
-200 regist.	0.108	0.103	0.102
	(0.31)	(0.30)	(0.30)
High school enrollm.	414.588	435.558	447.060
	(542.64)	(541.34)	(594.54)
High school classr.	12.815	13.290	13.595
	(17.17)	(16.86)	(18.34)
Socioeconomic Index	5.886	5.925	6.157
	(0.96)	(0.94)	(0.90)
Observations	8830	12579	24745

Notes: This table reports the average of school characteristics for the schools at the margin of UNICAMP's cutoffs. All the variables are available in the School Census. Panel A reports variables related to the school infrastructure, and Panel B reports the variables related to broader characteristics. The first column refers to our main sample, of the high schools that have never admitted a student to UNICAMP. The second column refers to the sample of high schools that did not have a former student admitted to UNICAMP in the past years. The third column refers to all high schools, regardless of past admissions to UNICAMP.

Table 2: Balancing Tests - all high schools

	(1) Teachers' class.	(2) Princ.' office	(3) Sci. lab	(4) Comp. lab	(5) Kitchen	(6) Sports c.	(7) Internet	(8) Waste coll.
Panel A: School infrastructure								
RD coef.	0.004	-0.020	0.007	0.004	-0.012	-0.018	0.005	-0.006
	(0.010)	(0.016)	(0.030)	(0.022)	(0.022)	(0.022)	(0.014)	(0.004)
Bandwidth	74.0	57.0	55.5	47.2	66.0	58.2	64.6	55.4
Observations	6,567	5,523	5,390	4,737	6,109	5,598	6,350	5,378
	SP	Urban	n. teachers	-200 regist	n. enrollm.	HS classr.	n. app. UNICAMP	
Panel B: School characteristics								
RD coef.	0.008	-0.000	0.373	0.001	13.394	0.489	-0.087	
	(0.024)	(0.005)	(0.965)	(0.017)	(27.840)	(0.891)	(0.088)	
Bandwidth	70.9	62.9	73.4	86.5	78.4	74.8	57.2	
Observations	6,450	5,938	6,439	6,534	6,796	6,585	15,251	

Notes: This table reports the balancing tests for the school variables. In Panel A we test variables related to school infrastructure and in Panel B we test other school characteristics. Except for the number of applications to UNICAMP – which comes from the admission database – all the variables are available in the School Census. We also report the optimal bandwidth and observations for each test. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 3: Balancing Tests - public high schools

	(1) Teachers' class.	(2) Princ.' office	(3) Sci. lab	(4) Comp. lab	(5) Kitchen	(6) Sports c.	(7) Internet	(8) waste coll.
Panel A: School infrastructure								
RD coef.	0.007	0.001	0.017	0.009	-0.003	0.000	0.026	-0.004
	(0.012)	(0.015)	(0.043)	(0.021)	(0.017)	(0.024)	(0.024)	(0.005)
Bandwidth	58.3	52.7	56.3	48.4	63.7	57.6	60.9	53.5
Observations	2,614	2,391	2,537	2,238	2,780	2,586	2,548	2,434
	SP	Urban	n. teachers	-200 regist	n. enrollm.	HS classr.	n. app. UNICAMP	
Panel B: School characteristics								
RD coef.	-0.029	0.011	0.186	0.009	51.324	1.790	0.043	
	(0.031)	(0.008)	(1.511)	(0.012)	(52.411)	(1.658)	(0.136)	
Bandwidth	61.1	51.5	72.1	51.0	61.6	59.1	54.9	
Observations	2,708	2,368	2,983	2,278	2,707	2,629	4,914	

Notes: This table reports the balancing tests for the school variables. In Panel A we test variables related to school infrastructure and in Panel B we test other school characteristics. Except for the number of applications to UNICAMP – which comes from the admission database – all the variables are available in the School Census. We also report the optimal bandwidth and observations for each test. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 4: Balancing Tests - private high schools

	(1) Teachers' class.	(2) Princ.' office	(3) Sci. lab	(4) Comp. lab	(5) Kitchen	(6) Sports c.	(7) Internet	(8) waste coll.
Panel A: School infrastructure								
RD coef.	-0.008	-0.030	-0.021	0.000	-0.002	-0.017	-0.004	-0.008
	(0.018)	(0.024)	(0.039)	(0.033)	(0.035)	(0.033)	(0.016)	(0.007)
Bandwidth	49.5	58.9	56.2	52.2	60.4	56.8	60.2	57.2
Observations	2,834	3,219	3,124	2,956	3,277	3,139	3,695	3,160
	SP	Urban	n. teachers	-200 regist	n. enrollm.	HS classr.	n. app. UNICAMP	
Panel B: School characteristics								
RD coef.	0.039	-0.008	0.642	-0.008	27.252	0.338	-0.144	
	(0.036)	(0.006)	(1.143)	(0.029)	(21.021)	(0.819)	(0.102)	
Bandwidth	61.0	59.5	65.5	83.0	80.9	65.7	68.7	
Observations	3,337	3,282	3,397	3,439	3,944	3,461	11,939	

Notes: This table reports the balancing tests for the school variables. In Panel A we test variables related to school infrastructure and in Panel B we test other school characteristics. Except for the number of applications to UNICAMP – which comes from the admission database – all the variables are available in the School Census. We also report the optimal bandwidth and observations for each test. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 5: Effects of older peers admission to UNICAMP on t+1 applications

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
LATE						
t+1 applications	0.443***	0.517**	0.353	0.105	0.466**	0.606**
	(0.167)	(0.216)	(0.246)	(0.330)	(0.208)	(0.268)
Bandwidth	54.6	70.1	52.7	51.5	53.7	74.3
First stage est.	0.423	0.416	0.402	0.412	0.435	0.425
First stage F-stat.	872.5	514.9	263.8	132.9	622.6	387.9
Observations	14,677	17,626	4,753	4,682	9,929	12,603

Notes: This table reports the LATE of older peers admission to UNICAMP on t+1 applications. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 6: Application averages for schools at the margin

	0 students adm.	0 students adm. (past 3 y.)	Regardless of past adm.
Panel A: All schools			
# applications in t	1.406	1.555	2.867
	(2.31)	(2.40)	(4.49)
# applications in t+1	1.029	1.207	2.636
	(2.62)	(2.81)	(5.33)
Delta applications (#(t+1) - #(t))	-0.377	-0.348	-0.231
	(2.21)	(2.41)	(3.98)
Observations	23597	29258	46101
Panel B: Public schools			
# applications in t	1.073	1.277	2.188
	(1.94)	(2.13)	(3.63)
# applications in t+1	0.771	0.986	1.934
	(2.30)	(2.42)	(3.93)
Delta applications (#(t+1) - #(t))	-0.303	-0.290	-0.255
	(2.07)	(2.14)	(2.82)
Observations	7899	9967	14181
Panel C: Private schools			
# applications in t	1.526	1.650	3.082
	(2.41)	(2.47)	(4.70)
# applications in t+1	1.115	1.272	2.851
	(2.70)	(2.92)	(5.66)
Delta applications (#(t+1) - #(t))	-0.411	-0.378	-0.231
	(2.21)	(2.47)	(4.23)
Observations	16336	19977	32663

Notes: This table reports the average in applications by school-year at the RDD margin, considering six samples, each of them as a combination of one Panel (Panel A: All schools, Panel B: Public schools, Panel C: Private schools) and one Column ('0 students admitted in the past', '0 students admitted in the past 3 years' and 'Regardless of past admissions'). Observations at the school level are provided at the end of each Panel.

Table 7: Effects on applications to other universities in t+1 (2000-2003) - all high schools

	(1) Only UNICAMP	(2) UNICAMP/USP	(3) UNICAMP/UNESP	(4) UNICAMP/USP/UNESP
Panel A: UNICAMP and other flagship universities in the State				
RD coef.	0.118	0.056	-0.019	0.034
	(0.078)	(0.078)	(0.025)	(0.125)
Bandwidth	64.0	55.5	72.9	49.5
First stage F-stat.	216.8	188.0	250.2	167.5
Observations	3,223	2,881	3,574	2,616
	UNICAMP/other private	UNICAMP/other public	UNICAMP/other pub. and priv.	
Panel B: UNICAMP and other options				
RD coef.	0.033	0.320***	0.231**	
	(0.039)	(0.107)	(0.094)	
Bandwidth	64.5	51.4	64.0	
First stage F-stat.	218.6	174.3	216.7	
Observations	3,251	2,697	3,222	

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 applications to other universities, from the survey question "Besides UNICAMP, which universities are you going to apply to this year?", available between 2000 and 2003. The effects are estimated semi-parametrically, using a local linear polynomial with a triangular kernel. Panel A reports the coefficients for the alternatives regarding "Only UNICAMP" and the other two flagship universities in the State. Panel B reports the coefficients for other three broader categories (UNICAMP and other private, UNICAMP and other public, UNICAMP and other private and public universities). We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 8: Effects on applications to other universities in t+1 (2000-2003) - public high schools

	(1) Only UNICAMP	(2) UNICAMP/USP	(3) UNICAMP/UNESP	(4) UNICAMP/USP/UNESP
Panel A: UNICAMP and other flagship universities in the State				
RD coef.	0.272	0.097	0.006	0.062
	(0.184)	(0.084)	(0.068)	(0.083)
Bandwidth	58.4	50.2	56.5	59.4
First stage F-stat.	53.4	47.3	52.0	54.1
Observations	905	799	882	921

	UNICAMP/other private	UNICAMP/other public	UNICAMP/other pub. and priv.
Panel B: UNICAMP and other options			
RD coef.	0.021	0.161*	0.078
	(0.052)	(0.092)	(0.096)
Bandwidth	52.9	56.4	51.2
First stage F-stat.	49.4	51.9	48.1
Observations	830	879	812

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 applications to other universities, from the survey question "Besides UNICAMP, which universities are you going to apply to this year?", available between 2000 and 2003. The effects are estimated semi-parametrically, using a local linear polynomial with a triangular kernel. Panel A reports the coefficients for the alternatives regarding "Only UNICAMP" and the other two flagship universities in the State. Panel B reports the coefficients for other three broader categories (UNICAMP and other private, UNICAMP and other public, UNICAMP and other private and public universities). We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 9: Effects on applications to other universities in t+1 (2000-2003) - private high schools

	(1) Only UNICAMP	(2) UNICAMP/USP	(3) UNICAMP/UNESP	(4) UNICAMP/USP/UNESP
Panel A: UNICAMP and other flagship universities in the State				
RD coef.	0.010	0.039	-0.028	0.041
	(0.068)	(0.088)	(0.022)	(0.156)
Bandwidth	61.3	62.2	74.4	53.8
First stage F-stat.	164.8	167.4	201.8	144.5
Observations	2,278	2,308	2,644	2,052
	UNICAMP/other private	UNICAMP/other public	UNICAMP/other pub. and priv.	
Panel B: UNICAMP and other options				
RD coef.	0.012	0.294**	0.229*	
	(0.047)	(0.123)	(0.118)	
Bandwidth	65.2	60.4	60.8	
First stage F-stat.	175.4	162.3	163.6	
Observations	2,400	2,251	2,268	

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 applications to other universities, from the survey question "Besides UNICAMP, which universities are you going to apply to this year?", available between 2000 and 2003. The effects are estimated semi-parametrically, using a local linear polynomial with a triangular kernel. Panel A reports the coefficients for the alternatives regarding "Only UNICAMP" and the other two flagship universities in the State. Panel B reports the coefficients for other three broader categories (UNICAMP and other private, UNICAMP and other public, UNICAMP and other private and public universities). We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 10: Effects of older peers admission to UNICAMP on t+1 applications - Informational channels

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
Samples						
pre-AA	0.542***	0.591**	0.435	0.439	0.555***	0.663**
	(0.183)	(0.239)	(0.267)	(0.299)	(0.209)	(0.282)
Bandwidth	65.5	80.7	61.3	107.8	73.0	87.6
Observations	9,049	10,580	3,047	4,381	6,812	7,730
Post-AA	0.193	0.233	0.209	0.017	0.162	0.222
	(0.318)	(0.399)	(0.524)	(0.677)	(0.428)	(0.560)
Bandwidth	49.2	69.3	73.9	55.2	46.7	60.9
Observations	5,585	7,093	2,278	1,915	3,587	4,420
Be. Med. Size	0.321	0.362	0.851	0.609	0.452	0.798
	(0.542)	(0.690)	(0.541)	(0.613)	(0.906)	(1.037)
Bandwidth	52.8	82.8	59.9	77.7	39.6	73.3
Observations	2,730	3,678	803	935	1,646	2,639
Ab. Med. Size	1.006*	1.025	0.104	-0.428	0.974	1.173
	(0.571)	(0.654)	(0.672)	(0.835)	(0.815)	(0.963)
Bandwidth	50.9	84.6	51.8	64.7	55.7	90.5
Observations	2,374	3,358	1,647	1,969	890	1,224
SP State	0.555**	0.595**	0.582	0.557	0.605*	0.729*
	(0.255)	(0.290)	(0.363)	(0.394)	(0.321)	(0.401)
Bandwidth	49.0	85.4	64.5	105.1	48.9	70.8
Observations	9,040	13,350	3,966	5,210	6,066	7,977
Out of SP State	0.298	0.305	0.119	0.128	0.230	0.307
	(0.212)	(0.247)	(0.241)	(0.292)	(0.240)	(0.293)
Bandwidth	46.8	80.1	49.7	79.7	63.1	96.7
Observations	3,465	5,204	1,092	1,537	3,177	4,152

Notes: This table reports the heterogeneous LATE of older peers' admission to UNICAMP on t+1 applications related to the informational channels. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage F-statistic, and observations for each column and panel. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 11: Effects of older peers admission to UNICAMP on t+1 applications: closer 'influencers' sample

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
LATE						
t+1 applications	0.772**	0.837**	0.285	0.321	0.636*	0.882*
	(0.333)	(0.372)	(0.589)	(0.665)	(0.364)	(0.469)
Bandwidth	52.2	95.7	70.8	90.0	57.0	76.9
First stage est.	0.436	0.429	0.357	0.366	0.465	0.462
First stage F-stat.	538.1	439.4	131.4	83.2	492.3	316.0
Observations	8,287	12,573	2,889	3,350	6,543	8,136

Notes: This table reports the LATE of older peers admission to UNICAMP on t+1 applications for the closer 'influencers' samples. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 12: Effects of older peers admission to UNICAMP on t+1 applications - major competitiveness

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
t+1 applications						
Below median comp.	0.413	0.457	0.904**	0.949**	0.320	0.388
	(0.261)	(0.305)	(0.380)	(0.449)	(0.294)	(0.359)
Bandwidth	62.8	103.8	81.1	114.4	67.7	104.8
First stage est.	0.377	0.373	0.321	0.324	0.408	0.403
First stage F-stat.	447.1	331.9	146.2	99.1	376.8	264.7
Observations	8,358	11,123	3,284	3,820	6,088	7,778
Above median comp.	0.386*	0.437*	-0.012	-0.216	0.468*	0.562*
	(0.226)	(0.250)	(0.310)	(0.348)	(0.264)	(0.329)
Bandwidth	39.7	79.2	62.6	70.1	52.4	85.0
First stage est.	0.470	0.456	0.499	0.475	0.472	0.449
First stage F-stat.	373.3	318.9	222.1	104.3	329.7	220.9
Observations	5,470	9,365	2,619	2,847	4,685	6,712

Notes: This table reports the LATE of older peers admission to UNICAMP on t+1 applications by major competitiveness. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column and panel. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 13: Effects of older peers admission to UNICAMP on t+1 admissions and enrollments

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
LATE						
Admissions: t+1	0.017	0.025	0.037	0.038	-0.009	0.010
	(0.027)	(0.030)	(0.031)	(0.036)	(0.030)	(0.040)
Bandwidth	50.3	88.6	54.6	90.4	71.8	88.7
First stage est.	0.421	0.413	0.401	0.395	0.446	0.424
First stage F-stat.	798.9	623.8	272.2	202.2	852.2	451.5
Observations	13,784	20,360	4,906	6,825	12,300	14,052
Enrollment: t+1	-0.049	-0.014	0.077	0.049	-0.091	-0.064
	(0.070)	(0.079)	(0.158)	(0.123)	(0.081)	(0.103)
Bandwidth	48.7	90.0	71.2	83.1	53.4	79.7
First stage est.	0.390	0.380	0.358	0.350	0.411	0.393
First stage F-stat.	324.1	259.3	133.9	71.0	263.4	165.8
Observations	6,742	10,311	2,896	3,178	4,933	6,546

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 admissions and enrollments at the same university. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column and panel. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table 14: Effects of older peers admission to UNICAMP on graduation

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
Graduation						
3 years after app.	0.006	0.008	-0.004	0.002	0.009	0.012
	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)
Bandwidth	46.9	87.9	58.0	73.6	55.8	90.0
Observations	6,511	10,192	2,505	2,954	5,116	7,030
4 years after app.	0.003	0.014	0.016	0.016	0.004	0.013
	(0.027)	(0.030)	(0.040)	(0.046)	(0.030)	(0.037)
Bandwidth	46.9	87.9	58.0	73.6	55.8	90.0
Observations	6,511	10,192	2,505	2,954	5,116	7,030
5 years after app.	-0.011	0.000	0.058	0.069	-0.046	-0.033
	(0.030)	(0.034)	(0.051)	(0.063)	(0.034)	(0.042)
Bandwidth	46.9	87.9	58.0	73.6	55.8	90.0
Observations	6,511	10,192	2,505	2,954	5,116	7,030
6 years after app.	-0.045	-0.042	-0.008	-0.023	-0.063*	-0.055
	(0.028)	(0.031)	(0.033)	(0.030)	(0.033)	(0.040)
Bandwidth	46.9	87.9	58.0	73.6	55.8	90.0
Observations	6,511	10,192	2,505	2,954	5,116	7,030

Notes: This table reports the LATE of older peers' admission to UNICAMP on graduation years after application at the same university. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column and panel. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

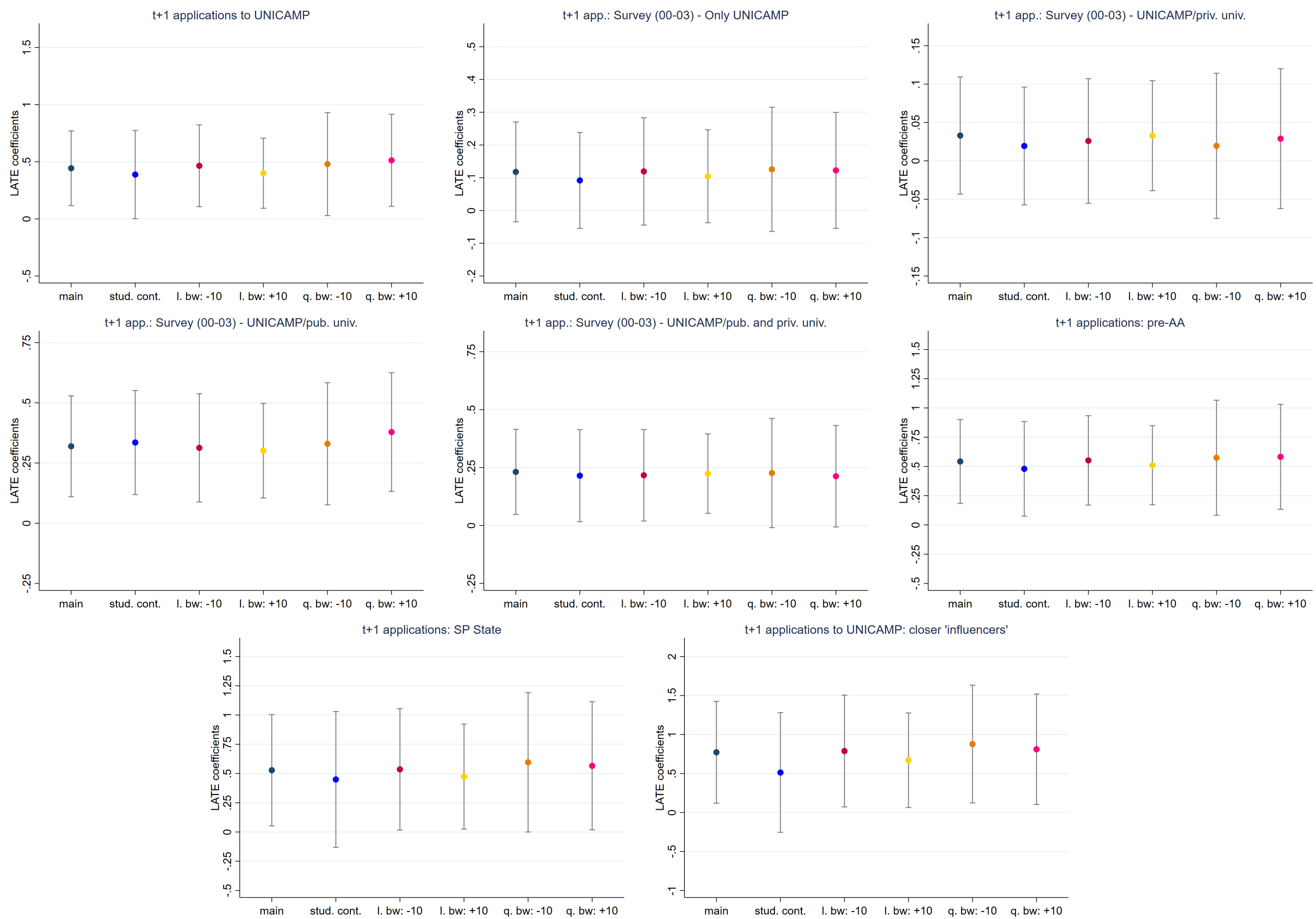
Table 15: Effects of older peers admission to UNICAMP on dropout

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
Dropout						
1 years after app.	-0.013*	-0.017*	-0.005	-0.007	-0.017*	-0.020
	(0.007)	(0.009)	(0.004)	(0.005)	(0.010)	(0.013)
Bandwidth	62.6	90.8	63.3	72.9	62.3	90.0
Observations	8,182	10,367	2,677	2,933	5,530	7,030
2 years after app.	0.007	0.010	0.038**	0.042	-0.004	-0.000
	(0.009)	(0.012)	(0.018)	(0.025)	(0.012)	(0.015)
Bandwidth	62.6	90.8	63.3	72.9	62.3	90.0
Observations	8,182	10,367	2,677	2,933	5,530	7,030
3 years after app.	-0.010	-0.015	-0.014	-0.019	-0.015	-0.021
	(0.010)	(0.013)	(0.024)	(0.035)	(0.012)	(0.015)
Bandwidth	62.6	90.8	63.3	72.9	62.3	90.0
Observations	8,182	10,367	2,677	2,933	5,530	7,030
4 years after app.	-0.007	-0.009	-0.005	-0.007	-0.005	-0.007
	(0.011)	(0.014)	(0.020)	(0.026)	(0.012)	(0.016)
Bandwidth	62.6	90.8	63.3	72.9	62.3	90.0
Observations	8,182	10,367	2,677	2,933	5,530	7,030
5 years after app.	0.001	0.000	-0.020	-0.034	0.009	0.011
	(0.006)	(0.008)	(0.015)	(0.022)	(0.007)	(0.009)
Bandwidth	62.6	90.8	63.3	72.9	62.3	90.0
Observations	8,182	10,367	2,677	2,933	5,530	7,030
6 years after app.	-0.009	-0.010	-0.005	-0.005	-0.011	-0.013
	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)	(0.011)
Bandwidth	62.6	90.8	63.3	72.9	62.3	90.0
Observations	8,182	10,367	2,677	2,933	5,530	7,030

Notes: This table reports the LATE of older peers' admission to UNICAMP on dropout, years after application at the same university. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column and panel. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

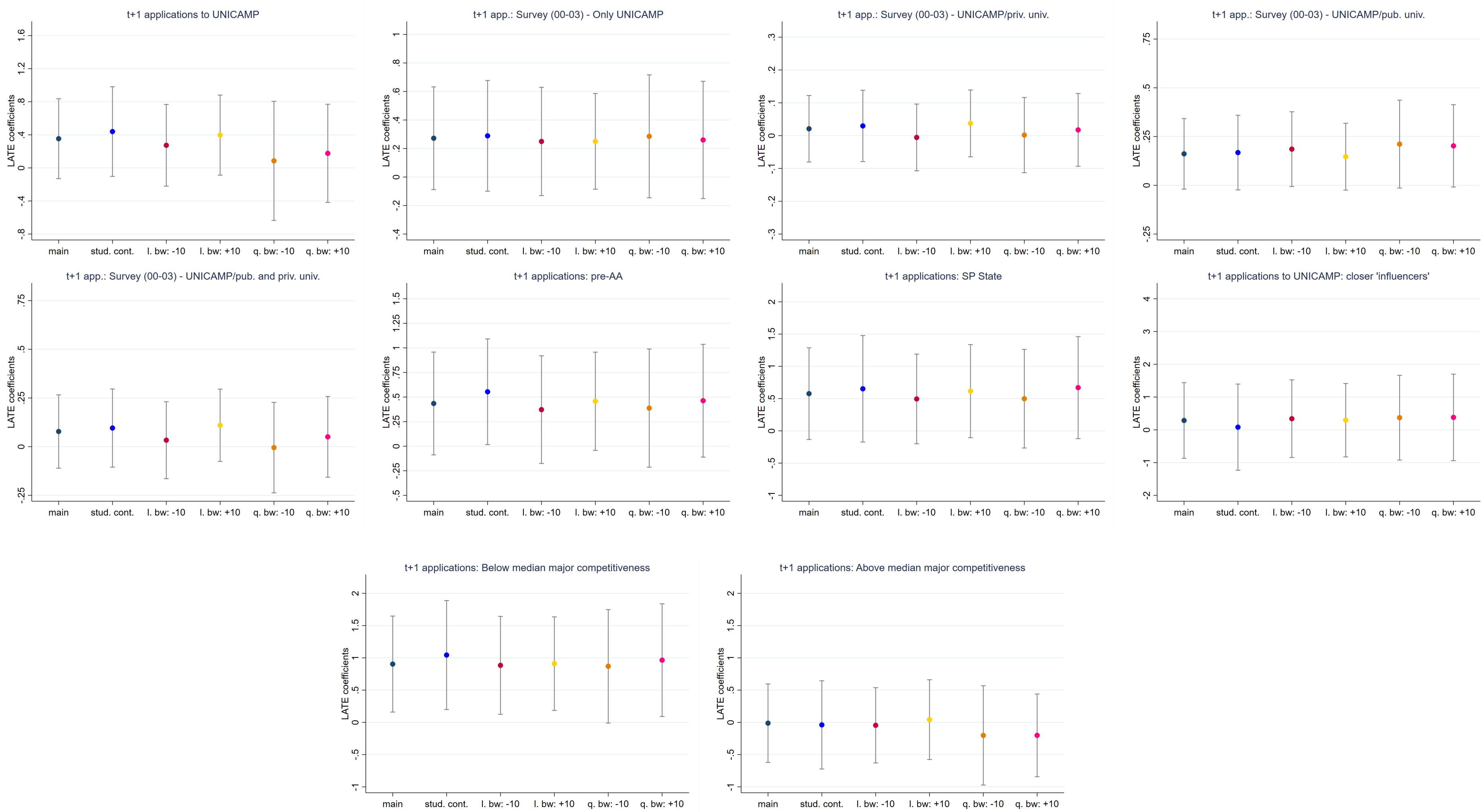
A Appendix Figures and Tables

Figure A.1: Robustness to Alternative Specifications - all high schools



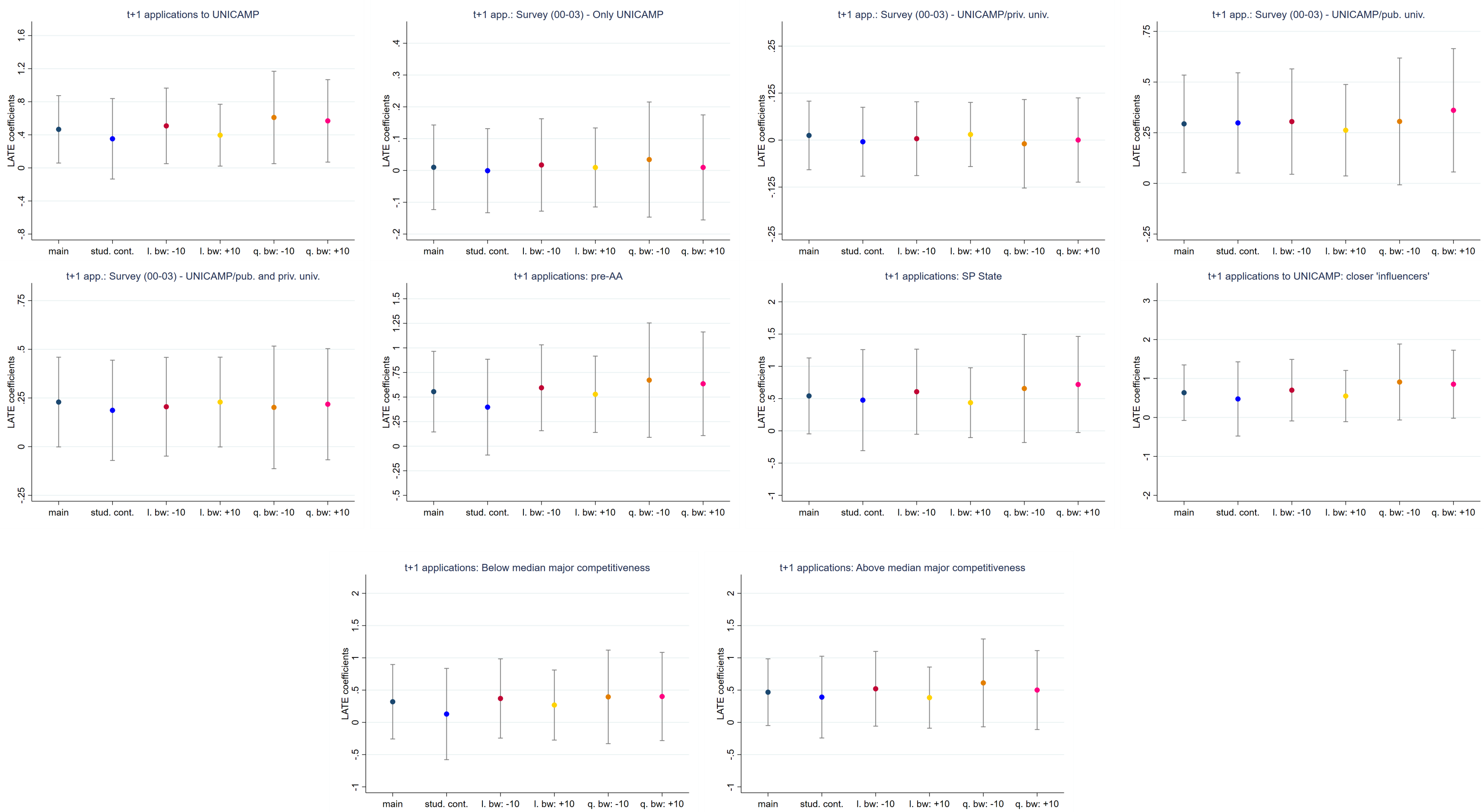
Notes: This figure reports the LATE of different outcomes used throughout the paper using different specifications – controlling for student characteristics and +-10-point distance from the original bandwidths in local linear and quadratic polynomials –, considering all high schools. The vertical bars refer to the 95% interval.

Figure A.2: Robustness to Alternative Specifications - public high schools



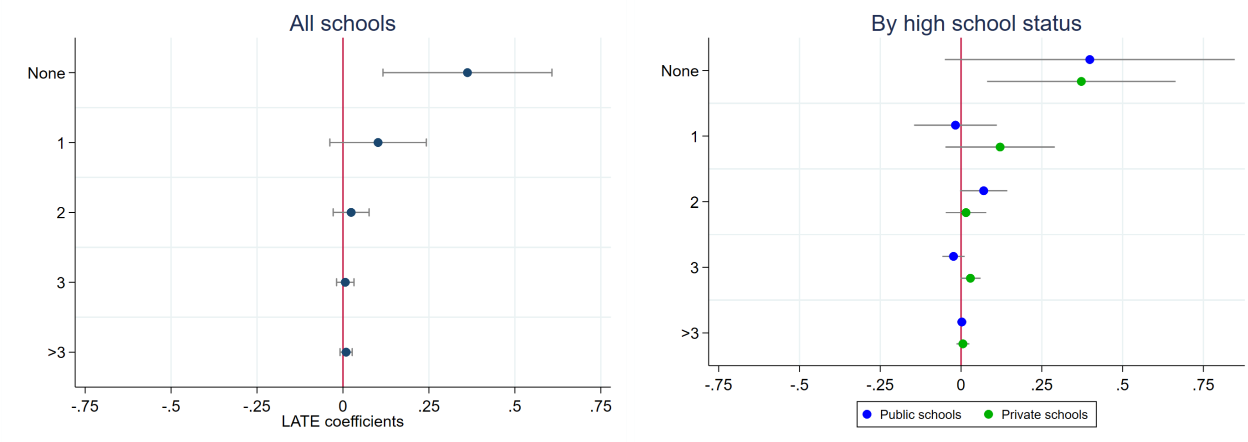
Notes: This figure reports the LATE of different outcomes used throughout the paper using different specifications – controlling for student characteristics and +-10-point distance from the original bandwidths in local linear and quadratic polynomials –, considering the public high schools. The vertical bars refer to the 95% interval.

Figure A.3: Robustness to Alternative Specifications - private high schools



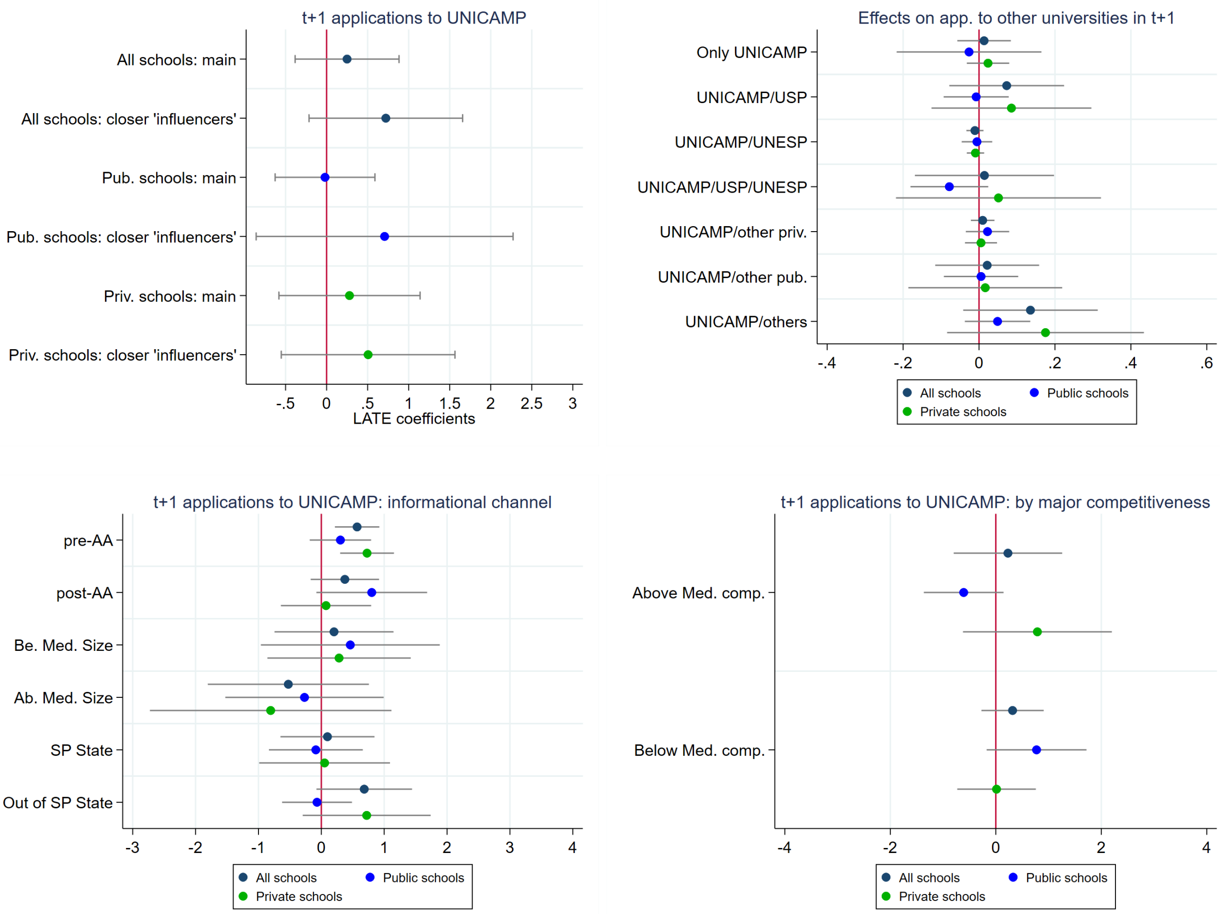
Notes: This figure reports the LATE of different outcomes used throughout the paper using different specifications – controlling for student characteristics and +-10-point distance from the original bandwidths in local linear and quadratic polynomials –, considering the private high schools. The vertical bars refer to the 95% interval.

Figure A.4: t+1 effects on newcomers - How many application exams have you done before (1990-2003)?



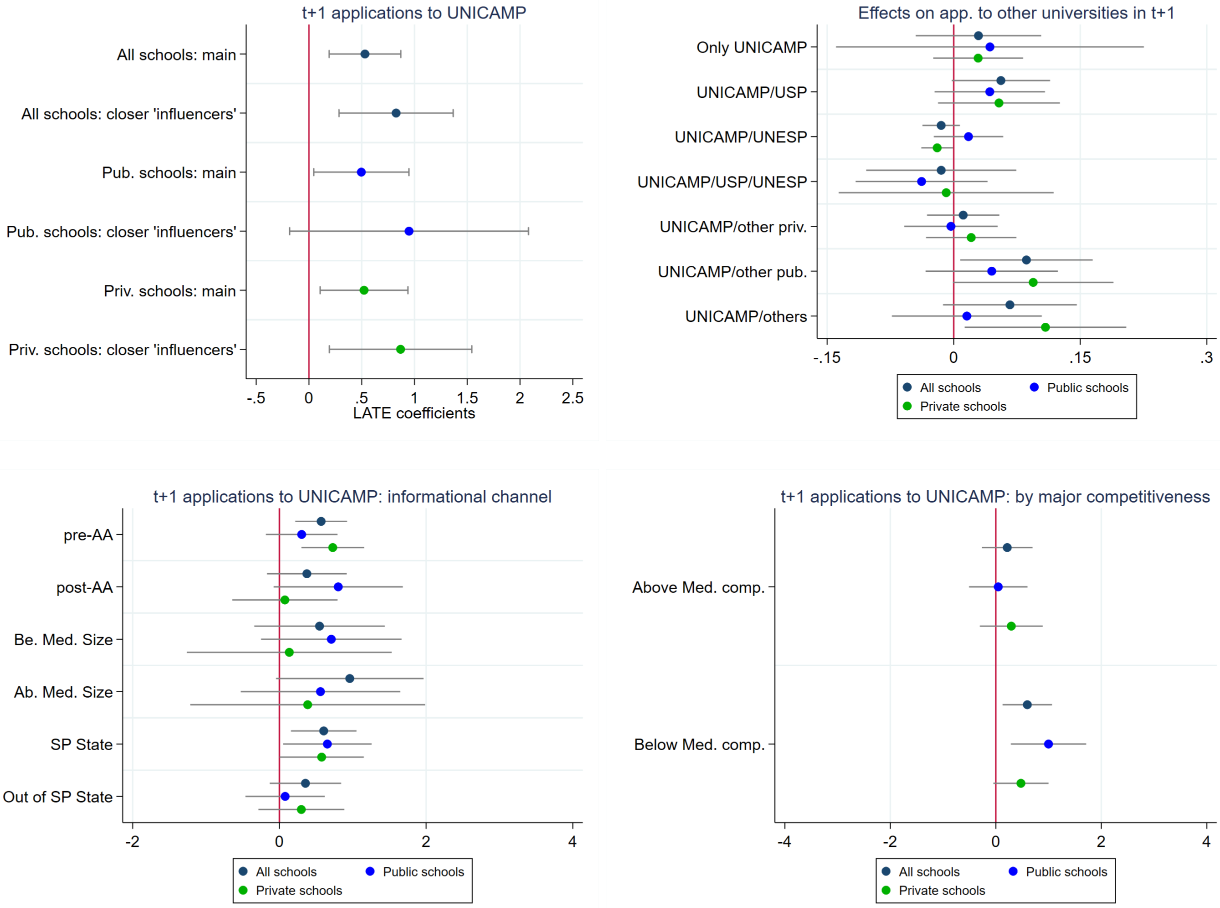
Notes: This figure reports the LATE of different alternatives asked in the UNICAMP's administrative survey. The question was "How many application exams have you done before?", available between 1990 and 2003). On the left, we consider all schools in the sample. On the right, we report the effect by high school status. The horizontal bars refer to the 95% interval.

Figure A.5: t+1 effects - regardless of past admissions



Notes: This figure reports the LATE of all outcomes using all the schools, regardless of the past admission history. On the upper left, we show the effects on t+1 applications to UNICAMP in the main specification and considering the closer 'influencers'. On the upper right, we show the effects on applications to other universities in t+1, as asked by the UNICAMP administrative survey. On the bottom left, we show the effects regarding the informational mechanism, and on the bottom right, we show the effects across major competitiveness. The horizontal bars refer to the 95% interval.

Figure A.6: t+1 effects - No past admission in the last three years



Notes: This figure reports the LATE of all outcomes using the sample of schools that did not have admissions to UNICAMP in the last three years. On the upper left, we show the effects on t+1 applications to UNICAMP in the main specification and considering the closer 'influencers'. On the upper right, we show the effects on applications to other universities in t+1, as asked by the UNICAMP administrative survey. On the bottom left, we show the effects regarding the informational mechanism, and on the bottom right, we show the effects across major competitiveness. The horizontal bars refer to the 95% interval.

Figure A.7: Social Media Activity - examples from public high schools

Notes: This figure illustrates the social media from a selected sample of public high schools in the last three years. In the first row, we show typical posts about commemorative dates (*Dia do Servidor Público*) and the school calendar (*Reunião de Pais e Responsáveis*). In the second row, we show the posts related to State and national evaluations (*OBMEP, Provão Paulista, Saresp, SAEB*), as well as those related to government programs (*Pé de Meia, QualificaSP*). In the third row are the posts related to admission exam information (SISU, ENEM, USP, UNESP, UNICAMP). In the last row, we show the only cases where the public high schools posted about their students' admission to higher education – specifically, to USP, UNESP, and UNICAMP. School names and students' faces were hidden on purpose.

Figure A.8: Social Media Activity - examples from private high schools

Notes: This figure illustrates the social media from a selected sample of private high schools in the last three years. In the first row, we show typical posts about commemorative dates (*Dia Mundial do Livro, Dia do Vestibulando*) and the school enrollment calendar (*"Matrículas abertas!"*). In the second row, are the posts related to admission exam information (ENEM, USP, Olimpíadas). In the last two rows, we show the typical posts of private high schools, about their students' admission to higher education. School names and students' faces were hidden on purpose.

Table A.1: Descriptive Statistics - public high schools

	0 students adm. (main)	0 students adm. past 3 y.	Regard. of past adm.
Panel A: School Infrastructure			
Teachers' room	0.978	0.980	0.980
	(0.15)	(0.14)	(0.14)
Principal's office	0.962	0.966	0.968
	(0.19)	(0.18)	(0.18)
Sciences lab	0.439	0.452	0.458
	(0.50)	(0.50)	(0.50)
Computer lab	0.935	0.943	0.945
	(0.25)	(0.23)	(0.23)
Kitchen	0.939	0.950	0.947
	(0.24)	(0.22)	(0.22)
Sports court	0.907	0.918	0.924
	(0.29)	(0.27)	(0.26)
Internet	0.899	0.900	0.909
	(0.30)	(0.30)	(0.29)
Waste collection	0.994	0.996	0.996
	(0.07)	(0.07)	(0.06)
Observations	4457	6236	9882
Panel B: School Characteristics			
SP State	0.811	0.836	0.866
	(0.39)	(0.37)	(0.34)
Urban	0.986	0.990	0.992
	(0.12)	(0.10)	(0.09)
Teachers	26.281	27.523	28.469
	(19.09)	(19.03)	(19.06)
-200 regist.	0.027	0.029	0.028
	(0.16)	(0.17)	(0.16)
High school enrollm.	642.293	673.348	763.986
	(630.98)	(619.71)	(719.74)
High school classr.	18.617	19.332	21.889
	(19.61)	(19.09)	(22.19)
Socioeconomic Index	5.252	5.280	5.372
	(0.80)	(0.76)	(0.73)
Observations	4150	5920	9551

Notes: This table reports the average of school characteristics for the schools at the margin of UNICAMP's cutoffs. All the variables are available in the School Census. Panel A reports variables related to the school infrastructure, and Panel B reports the variables related to broader characteristics. The first column refers to our main sample, of the high schools that have never admitted a student to UNICAMP. The second column refers to the sample of high schools that did not have a former student admitted to UNICAMP in the past years. The third column refers to all high schools, regardless of past admissions to UNICAMP.

Table A.2: Descriptive Statistics - private high schools

	0 students adm. (main)	0 students adm. past 3 y.	Regard. of past adm.
Panel A: School Infrastructure			
Teachers' room	0.958	0.963	0.966
	(0.20)	(0.19)	(0.18)
Principal's office	0.886	0.900	0.904
	(0.32)	(0.30)	(0.29)
Sciences lab	0.607	0.629	0.654
	(0.49)	(0.48)	(0.48)
Computer lab	0.759	0.767	0.784
	(0.43)	(0.42)	(0.41)
Kitchen	0.698	0.714	0.723
	(0.46)	(0.45)	(0.45)
Sports court	0.753	0.768	0.785
	(0.43)	(0.42)	(0.41)
Internet	0.940	0.942	0.955
	(0.24)	(0.23)	(0.21)
Waste collection	0.991	0.991	0.990
	(0.10)	(0.10)	(0.10)
Observations	6173	8396	17494
Panel B: School Characteristics			
SP State	0.619	0.604	0.688
	(0.49)	(0.49)	(0.46)
Urban	0.995	0.996	0.996
	(0.07)	(0.07)	(0.06)
Teachers	17.170	18.108	18.964
	(16.71)	(17.57)	(17.83)
-200 regist.	0.183	0.174	0.153
	(0.39)	(0.38)	(0.36)
High school enrollm.	227.749	234.874	252.846
	(370.73)	(366.16)	(387.87)
High school classr.	8.044	8.205	8.521
	(13.12)	(12.83)	(13.07)
Socioeconomic Index	6.554	6.595	6.707
	(0.61)	(0.59)	(0.53)
Observations	5108	7140	15752

Notes: This table reports the average of school characteristics for the schools at the margin of UNICAMP's cutoffs. All the variables are available in the School Census. Panel A reports variables related to the school infrastructure, and Panel B reports the variables related to broader characteristics. The first column refers to our main sample, of the high schools that have never admitted a student to UNICAMP. The second column refers to the sample of high schools that did not have a former student admitted to UNICAMP in the past years. The third column refers to all high schools, regardless of past admissions to UNICAMP.

Table A.3: Balancing Tests - student characteristics

	(1) FV Index	(2) IV Index	(3) Vulnerability Index
Panel A: All schools			
RD coef.	0.017	0.008	0.013
	(0.012)	(0.008)	(0.009)
Bandwidth	62.4	48.3	52.0
Observations	12,291	13,141	10,662
Panel B: Public schools			
RD coef.	0.016	0.013	0.012
	(0.022)	(0.015)	(0.016)
Bandwidth	58.2	45.3	51.4
Observations	3,980	4,145	3,603
Panel C: Private schools			
RD coef.	0.015	0.005	0.011
	(0.013)	(0.007)	(0.008)
Bandwidth	62.0	65.0	62.2
Observations	8,371	11,356	8,383

Notes: This table reports the balancing tests for the student characteristics, summarized by three indexes: Family Vulnerability Index, Individual Vulnerability Index, and the total Vulnerability Index. All the variables used to construct those indexes are available in the UNICAMP Survey taken by all the students at the moment of the exam registration. We report the optimal bandwidth and observations for each test. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.4: Effects on applications to other universities in t+1 (2000-2003) - all high schools

	(1) Only UNICAMP	(2) UNICAMP/USP	(3) UNICAMP/UNESP	(4) UNICAMP/USP/UNESP
Panel A: UNICAMP and other flagship universities in the State				
RD coef.	0.122	0.070	-0.019	0.056
	(0.093)	(0.092)	(0.030)	(0.133)
Bandwidth	95.8	88.6	108.0	99.7
First stage F-stat.	143.7	134.4	158.4	148.1
Observations	4,168	3,999	4,423	4,256
	UNICAMP/other private	UNICAMP/other public	UNICAMP/other pub. and priv.	
Panel B: UNICAMP and other options				
RD coef.	0.023	0.355***	0.225*	
	(0.047)	(0.126)	(0.115)	
Bandwidth	87.5	74.9	94.3	
First stage F-stat.	132.8	117.8	141.9	
Observations	3,973	3,631	4,140	

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 applications to other universities, from the survey question "Besides UNICAMP, which universities are you going to apply to this year?", available between 2000 and 2003. The effects are estimated semi-parametrically, using a local quadratic polynomial with a triangular kernel. Panel A reports the coefficients for the alternatives regarding "Only UNICAMP" and the other two flagship universities in the State. Panel B reports the coefficients for other three broader categories (UNICAMP and other private, UNICAMP and other public, UNICAMP and other private and public universities). We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.5: Effects on applications to other universities in t+1 (2000-2003) - public high schools

	(1) Only UNICAMP	(2) UNICAMP/USP	(3) UNICAMP/UNESP	(4) UNICAMP/USP/UNESP
Panel A: UNICAMP and other flagship universities in the State				
RD coef.	0.281	0.103	0.001	0.068
	(0.214)	(0.090)	(0.074)	(0.094)
Bandwidth	82.4	87.8	102.4	98.1
First stage F-stat.	36.5	38.0	42.2	40.6
Observations	1,166	1,202	1,302	1,272
	UNICAMP/other private	UNICAMP/other public	UNICAMP/other pub. and priv.	
Panel B: UNICAMP and other options				
RD coef.	0.010	0.201*	0.029	
	(0.057)	(0.110)	(0.111)	
Bandwidth	86.9	84.3	75.0	
First stage F-stat.	37.7	37.1	33.7	
Observations	1,198	1,181	1,099	

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 applications to other universities, from the survey question "Besides UNICAMP, which universities are you going to apply to this year?", available between 2000 and 2003. The effects are estimated semi-parametrically, using a local quadratic polynomial with a triangular kernel. Panel A reports the coefficients for the alternatives regarding "Only UNICAMP" and the other two flagship universities in the State. Panel B reports the coefficients for other three broader categories (UNICAMP and other private, UNICAMP and other public, UNICAMP and other private and public universities). We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.6: Effects on applications to other universities in t+1 (2000-2003) - private high schools

	(1) Only UNICAMP	(2) UNICAMP/USP	(3) UNICAMP/UNESP	(4) UNICAMP/USP/UNESP
Panel A: UNICAMP and other flagship universities in the State				
RD coef.	0.019	0.025	-0.064**	0.076
	(0.088)	(0.116)	(0.030)	(0.179)
Bandwidth	75.0	80.5	70.1	94.8
First stage F-stat.	93.1	98.1	88.5	113.2
Observations	2,657	2,770	2,520	3,047

	UNICAMP/other private	UNICAMP/other public	UNICAMP/other pub. and priv.
Panel B: UNICAMP and other options			
RD coef.	-0.003	0.340**	0.217
	(0.059)	(0.155)	(0.153)
Bandwidth	78.5	78.7	81.1
First stage F-stat.	96.3	96.5	98.6
Observations	2,738	2,743	2,782

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 applications to other universities, from the survey question "Besides UNICAMP, which universities are you going to apply to this year?", available between 2000 and 2003. The effects are estimated semi-parametrically, using a local quadratic polynomial with a triangular kernel. Panel A reports the coefficients for the alternatives regarding "Only UNICAMP" and the other two flagship universities in the State. Panel B reports the coefficients for other three broader categories (UNICAMP and other private, UNICAMP and other public, UNICAMP and other private and public universities). We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.7: Balancing tests - by sample: all high schools

	(1) Fam. V. Index	(2) Ind. V. Index	(3) Student Vuln. Index	(4) Infra. V. Index	(5) Teaching V. Index	(6) School Vuln. Index
Panel A: Information channel						
Pre-AA	0.021	0.010	0.016	0.012	-0.003	0.012
	(0.015)	(0.010)	(0.011)	(0.017)	(0.020)	(0.013)
Post-AA	0.013	-0.001	0.008	-0.002	-0.015	-0.001
	(0.021)	(0.011)	(0.014)	(0.016)	(0.016)	(0.013)
Ab. Med. Size	0.030	0.001	0.020	0.011	-0.024	0.002
	(0.030)	(0.020)	(0.022)	(0.013)	(0.016)	(0.011)
Be. Med. Size	-0.013	-0.007	-0.010	0.007	0.013	0.015
	(0.026)	(0.014)	(0.016)	(0.020)	(0.015)	(0.015)
SP State	0.015	0.004	0.010	0.004	-0.022*	0.002
	(0.015)	(0.010)	(0.012)	(0.016)	(0.013)	(0.011)
Out of SP State	-0.001	0.017	0.009	0.012	0.036*	0.017
	(0.022)	(0.012)	(0.012)	(0.015)	(0.021)	(0.013)
Panel B: 'ability' proximity						
closer 'influencers'	0.011	0.001	0.010	0.025*	0.000	0.019*
	(0.015)	(0.009)	(0.010)	(0.015)	(0.014)	(0.011)
Ab. major comp.	0.020	0.009	0.018	-0.007	0.005	0.012
	(0.017)	(0.009)	(0.011)	(0.021)	(0.017)	(0.015)
Be. major comp.	-0.004	-0.005	-0.006	0.017	-0.010	0.007
	(0.017)	(0.011)	(0.012)	(0.014)	(0.015)	(0.011)
N	11416	14563	11368	4775	5786	4477

Notes: This table reports the balancing tests for the school and students' vulnerability indexes by sample used in the mechanism section, considering all high schools. In Panel A are the samples related to the informational mechanism. In Panel B are the samples related to the 'ability' proximity mechanism. All the variables used to construct the index come from the School Census or the UNICAMP's administrative survey. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.8: Balancing tests - by sample: public high schools

	(1) Fam. V. Index	(2) Ind. V. Index	(3) Student Vuln. Index	(4) Infra. V. Index	(5) Teaching V. Index	(6) School Vuln. Index
Panel A: Information channel						
Pre-AA	0.020	0.033	0.023	-0.006	-0.024	-0.016
	(0.029)	(0.021)	(0.023)	(0.018)	(0.028)	(0.014)
Post-AA	-0.000	-0.012	-0.002	-0.005	-0.031	-0.006
	(0.036)	(0.020)	(0.024)	(0.019)	(0.024)	(0.014)
Ab. Med. Size	0.030	0.002	0.013	-0.002	-0.040**	-0.013
	(0.030)	(0.023)	(0.023)	(0.012)	(0.018)	(0.011)
Be. Med. Size	-0.004	-0.005	-0.023	0.011	-0.004	-0.001
	(0.054)	(0.030)	(0.038)	(0.030)	(0.034)	(0.021)
SP State	0.019	0.012	0.011	-0.011	-0.034**	-0.018
	(0.022)	(0.017)	(0.017)	(0.014)	(0.016)	(0.011)
Out of SP State	0.002	0.016	0.008	0.028	0.015	0.038*
	(0.044)	(0.024)	(0.028)	(0.026)	(0.034)	(0.021)
Panel B: 'ability' proximity						
closer 'influencers'	0.005	0.024	0.016	0.028	-0.010	0.026*
	(0.028)	(0.019)	(0.017)	(0.018)	(0.021)	(0.013)
Ab. major comp.	0.035	0.015	0.021	0.002	-0.060**	-0.019
	(0.032)	(0.018)	(0.022)	(0.021)	(0.030)	(0.015)
Be. major comp.	-0.007	0.013	0.001	-0.008	-0.026	-0.005
	(0.025)	(0.020)	(0.020)	(0.015)	(0.022)	(0.012)
N	3917	4896	3894	2191	2725	2102

Notes: This table reports the balancing tests for the school and students' vulnerability indexes by sample used in the mechanism section, considering the public high schools. In Panel A are the samples related to the informational mechanism. In Panel B are the samples related to the 'ability' proximity mechanism. All the variables used to construct the index come from the School Census or the UNICAMP's administrative survey. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.9: Balancing tests - by sample: private high schools

	(1) Fam. V. Index	(2) Ind. V. Index	(3) Student Vuln. Index	(4) Infra. V. Index	(5) Teaching V. Index	(6) School Vuln. Index
Panel A: Information channel						
Pre-AA	0.019	0.007	0.011	0.019	0.033	0.034
	(0.016)	(0.009)	(0.011)	(0.029)	(0.026)	(0.022)
Post-AA	0.022	0.003	0.017	0.006	-0.003	0.010
	(0.022)	(0.010)	(0.013)	(0.022)	(0.020)	(0.018)
Ab. Med. Size	0.070	0.009	0.071**	0.036	0.019	0.029
	(0.047)	(0.023)	(0.033)	(0.030)	(0.028)	(0.023)
Be. Med. Size	-0.019	0.004	-0.008	0.009	0.021	0.021
	(0.027)	(0.013)	(0.016)	(0.023)	(0.016)	(0.017)
SP State	0.021	0.005	0.013	0.011	-0.002	0.015
	(0.017)	(0.009)	(0.011)	(0.025)	(0.018)	(0.020)
Out of SP State	-0.012	0.010	0.007	0.003	0.068**	0.017
	(0.026)	(0.009)	(0.013)	(0.019)	(0.029)	(0.015)
Panel B: 'ability' proximity						
closer 'influencers'	0.014	-0.006	0.006	0.025	0.006	0.018
	(0.014)	(0.007)	(0.008)	(0.021)	(0.017)	(0.016)
Ab. major comp.	0.013	0.003	0.010	-0.010	0.011	0.021
	(0.018)	(0.009)	(0.011)	(0.028)	(0.024)	(0.020)
Be. major comp.	0.005	-0.003	-0.001	0.029	0.033*	0.022
	(0.018)	(0.009)	(0.012)	(0.024)	(0.019)	(0.019)
N	7744	9992	7716	2486	2847	2252

Notes: This table reports the balancing tests for the school and students' vulnerability indexes by sample used in the mechanism section, considering the private high schools. In Panel A are the samples related to the informational mechanism. In Panel B are the samples related to the 'ability' proximity mechanism. All the variables used to construct the index come from the School Census or the UNICAMP's administrative survey. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.10: Effects of older peers admission to UNICAMP on younger cohorts applications

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
LATE						
cohort grad. in t+2	0.602**	0.648**	0.146	0.054	0.615*	0.721*
	(0.278)	(0.305)	(0.301)	(0.379)	(0.332)	(0.386)
Bandwidth	45.1	82.8	49.8	64.9	53.1	88.5
First stage est.	0.421	0.416	0.401	0.408	0.438	0.429
First stage F-stat.	708.2	583.6	244.2	157.0	614.8	452.4
Observations	12,292	19,206	4,429	5,419	9,688	13,781
cohort grad. in t+3	0.874*	0.935*	0.313	0.072	1.032	1.091
	(0.490)	(0.521)	(0.326)	(0.401)	(0.634)	(0.678)
Bandwidth	45.9	90.0	41.4	58.7	49.5	97.0
First stage est.	0.419	0.414	0.403	0.409	0.437	0.430
First stage F-stat.	699.3	609.1	203.0	140.3	561.0	484.1
Observations	12,258	19,778	3,724	4,925	9,003	14,252

Notes: This table reports the LATE of older peers' admission to UNICAMP on younger cohorts applications (those graduating from high school in t+2 and t+3), in the first year they get a chance to be accepted. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.11: Effects of older peers admission to UNICAMP on the next immediate cohort applications in t+2 and t+3

	Overall		Public Schools		Private Schools	
	(1) local lin.	(2) local quad.	(3) local lin.	(4) local quad.	(5) local lin.	(6) local quad.
LATE						
t+2 applications	0.221	0.279	0.441	0.385	0.097	0.113
	(0.199)	(0.238)	(0.370)	(0.412)	(0.235)	(0.269)
Bandwidth	57.1	91.7	61.7	106.2	58.4	109.8
First stage est.	0.395	0.380	0.357	0.342	0.415	0.399
First stage F-stat.	387.8	264.0	117.0	84.0	292.9	229.0
Observations	7,699	10,423	2,624	3,593	5,297	7,759
t+3 applications	0.030	0.009	-0.042	-0.040	0.033	0.049
	(0.117)	(0.134)	(0.245)	(0.296)	(0.122)	(0.150)
Bandwidth	59.1	106.7	79.5	90.1	58.5	92.3
First stage est.	0.396	0.380	0.359	0.349	0.415	0.395
First stage F-stat.	402.7	303.3	147.4	75.9	293.2	192.4
Observations	7,876	11,206	3,083	3,325	5,298	7,130

Notes: This table reports the LATE of older peers' admission to UNICAMP on the next immediate cohort applications in t+2 and t+3. The effects are estimated semi-parametrically, using local linear (odd columns) and quadratic polynomials (even columns) with a triangular kernel. Columns 1 and 2 consider all high schools, 3 and 4 only the public high schools, and 5 and 6 the private high schools. We report the optimal bandwidth, the first-stage estimates, the first-stage F-statistic, and observations for each column. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.

Table A.12: Effects on applications to other universities in t+1

	(1) USP (99-17)	(2) UNICAMP/USP (99-17)	(3) UNESP(01-03)	(4) UNICAMP/USP/UNESP (01-03)
LATE				
All high schools	0.010	0.027	-0.011	-0.072
	(0.045)	(0.075)	(0.037)	(0.137)
Bandwidth	45.6	46.4	44.9	51.8
First stage F-stat.	400.7	407.6	146.3	161.6
Observations	8,811	8,960	2,947	2,016
Public high schools	0.071	0.149	0.003	-0.006
	(0.049)	(0.095)	(0.027)	(0.061)
Bandwidth	62.9	50.0	65.6	42.1
First stage F-stat.	158.8	128.4	68.4	41.0
Observations	3,492	2,939	1,187	517
Private high schools	-0.013	-0.032	-0.019	-0.102
	(0.058)	(0.096)	(0.047)	(0.179)
Bandwidth	47.1	47.2	44.9	53.2
First stage F-stat.	296.2	297.0	116.8	126.8
Observations	6,332	6,341	2,159	1,508

Notes: This table reports the LATE of older peers' admission to UNICAMP on t+1 admissions to other public flagship universities. The effects are estimated semi-parametrically, using a local quadratic polynomial with a triangular kernel. Panel A reports the coefficients for all high schools in the sample. Panel B reports the coefficients for public high schools. Panel C reports the coefficients for private high schools. We report the optimal bandwidth, the first-stage F-statistic, and observations for each alternative. Standard errors clustered at the school level are reported in parentheses. ***, **, and * indicate the coefficients significantly different from zero at the 99, 95, and 90 percent confidence levels.