# The Long-Term Effect of Admission to a Top-Quality University on Crime*

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**Abstract**

We investigate the effect of attending a top-quality, tuition-free university on future criminal charges. Using data on students' application to a public university and the universe of criminal records in Brazil, we document that admitted students are 69% less likely to be prosecuted in the decade following application. This effect is mostly driven by a reduction in violent crimes among low-income students. Changes in educational attainment, incapacitation, financial distress, unemployment, and earnings do not explain our findings. Our results suggest that the returns to expanding access of low-income students to high quality universities extend far beyond job opportunities.

**JEL codes**: D91, I23, H52, K42

**Keywords**: Crime, Higher Education, Affordability, Social Mobility

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# 1 Introduction

To what extent can access to a selective university change someone's life? According to Hoxby and Avery (2013) and Chetty et al. (2020), enrollment in a top-quality school is crucial for talented students in low- and middle-income groups to find better job opportunities and experience social mobility. Yet expanding access to more selective higher education (HE) institutions may impact more than career prospects. It may also affect socio-emotional competencies, breaking the intergenerational transmission of criminal and violent behavior (Hjalmarsson and Lindquist, 2012).

Since Lochner and Moretti's (2004) seminal evidence for causal effects, a large body of research has documented that education reduces crime. However, this effect may happen through different mechanisms. On the one hand, education occupies the youth, increases wages, and reduces the risk of unemployment, hence increasing the opportunity cost of committing crimes (Becker, 1968). On the other hand, schools can directly influence criminal and violent behavior by shaping self-regulatory skills (Loewenstein, 2000; Cunha, Heckman and Schennach, 2010; Durlak et al., 2011). Still, identifying the link through which education affects criminal behavior is challenging due to the lack of individual-level data on crime, combined with the proper empirical setting to estimate causal effects.

In this paper, we investigate the effect of attending a top-quality public university in Northeast Brazil on the criminal prosecution of students from distinct socioeconomic groups. Given its high quality, reputation, and tuition-free policy, this university is one of the top choices for students in the region, but it usually accepts only 10% of the applicants. For each university applicant in 2006 and 2007, we follow the courses of criminal charges, registered employment, and salaries over ten years. To identify causal effects, we exploit a discontinuity in the admission process, which is strictly based on a test score. Accordingly, we compare applicants just above the admission cutoff for each program of study with the ones just below. For the sake of identification, three aspects are essential in this setting: applicants may apply to only one undergraduate program in the university per year; they must take the admission exam all at the same time; and the admission cutoff is revealed after the exam. These aspects prevent students from manipulating the admission process and provide considerable variation across programs of study.

Studying the relationship between access to HE and crime in Brazil is particularly appealing because criminal activity is considered an epidemic in this country.[1] It has the highest number of homicides in the world, as well as 14 of the 50 most violent cities.[2] Ten of these cities are in the same region as the university that we study. Moreover, basic educational opportunities are quite unequal across socioeconomic groups (Ferreira and Gignoux, 2013), which is confirmed by the Program for International Student Assessment (PISA). Whereas private schools predominantly attended by high-income students score well above the OECD average in reading, mathematics, and science, most public schools score at the bottom of the worldwide ranking in the three subjects (Fontanive et al., 2021). When it comes to HE, though, public universities are highly selective and attract applicants from a wide range of socioeconomic status (SES). In addition to their high quality and reputation, these universities do not charge tuition fees. As a result, they provide the opportunity for high-performing students from low-income families to attend highly selective universities. In the process, students from different backgrounds, including different school systems, are immersed into a common learning environment.

From the pool of applicants to the public university, about 3% face criminal charges in the following decade. Among low-income applicants, the rate is close to 6%. If admitted, our estimates show that the likelihood of students facing criminal prosecution decreases by 2.5 percentage points (p.p.), or 69% relative to the baseline rate. This effect is mainly driven by a reduction among low-income students, whose chances of prosecution decrease by 4.4 p.p. (or 77%) after admission. Further, we show that the effect is large and significant only for low-income applicants enrolled in programs with a large presence of high-income students,

[1]The World Health Organization classifies ten homicides per 100,000 inhabitants as an epidemic. The rate in Brazil is around 30 homicides/100,000 inhabitants. Sources: www.latinamerica.undp.org and www.worldbank.org.

[2]Sources: United Nations Office on Drugs and Crime (UNODC) and WorldAtlas.com.

which we refer to as 'high' SES programs. For the high-income group, we find a reduction of 0.9 p.p. (or 81%), which is statistically insignificant.

As regards the type of crime, most of the effect in the low-income group happens through the reduction in violent crime. In the high-income group, we observe significant reductions in traffic-related crimes, such as reckless driving and driving under the influence (DUI), and crimes against the public interest, such as drug-related crimes, corruption, and tax evasion. The differential effects between groups are consistent with the fact that high- and low-income students have very different baseline measures of prosecution across different crimes.

In terms of mechanisms, we find that admission to the public university increases low-income students' probability of graduating from college by 8.9 p.p. and their future earnings by almost 25%. However, the effect of admission on criminal prosecution is unrelated to labor market outcomes or educational attainment. One reason is that the impacts on college graduation, formal employment, and work experience are not large enough to affect criminal behavior.[3] Indeed, the effect on crime for both income groups remains nearly the same after controlling for those outcomes. Furthermore, the group of students exhibiting lower criminal activity presents small and insignificant gains in salary. For all the subsamples we examine, the effect on future earnings is meaningful and significant only for low-income students enrolled in low SES programs. For this group, though, the effect on criminal charges is neither large nor significant.

Still, one may argue that our findings are unrelated to changes in criminal behavior. Instead, by interacting with wealthier students, low-income students might learn how to avoid prosecution after committing a crime. If this hypothesis were true, we should not observe significant reductions in the types of crime committed by high-income students. Furthermore, we find that admission to the public university does not protect high- and low-income students from civil lawsuits (e.g., contract litigation, fraud litigation, evictions, and divorces).

[3] The effect of admission on educational attainment is not higher because the studied period coincides with the expansion of a student loan program in Brazil named FIES (*Fundo de Financiamento Estudantil*), which helped low-income students to pay for private institutions.

Finally, assuming that law school applicants are more sensitive to the learning channel, we reestimate the effect on criminal prosecution excluding them from the sample. If anything, the effect becomes slightly stronger. Although we cannot disregard that students may learn from each other how to avoid prosecution, this mechanism does not appear consistently across our results.

Additional findings reveal that the effect on criminal charges starts when students transition from college to the labor market, is not exclusive to men, and is unrelated to an incapacitation mechanism. Besides, admission to the public university has no significant effects on migration and legal distress caused by a divorce or unpaid debt. Nevertheless, gains in institutional quality appear to be consistent with the impact on low-income students enrolled in high SES programs. Due to admission, these students are 71 p.p. more likely to graduate from a high-quality institution.[4] For the other groups, gains in educational quality are smaller.

The present work is closely related to two threads of the literature. The first is on the relationship between education and crime (Lochner and Moretti, 2004; Buonanno and Leonida, 2009; Machin, Marie and Vujić, 2011; Bennett, 2018).[5] The second is on the role of social determinants in criminal behavior (Kling, Ludwig and Katz, 2005; Bayer, Hjalmarsson and Pozen, 2009; Drago and Galbiati, 2012; Corno, 2017; Stevenson, 2017; Dustmann and Landersø, 2021; Billings and Schnepel, 2022). The present study contributes to this literature by showing that part of the impact of school quality on crime goes far beyond educational attainment and labor market opportunities. Although we cannot pinpoint the exact channel for the effects on criminal behavior, our results seem rather consistent with the idea that self-regulatory skills are malleable during early adulthood and respond to immersion into an outgroup SES environment.

More broadly, our findings are also consistent with Chetty et al. (2022) who find that

[4] The Brazilian Ministry of Education assesses institutional quality and classifies universities and programs of study as low-, medium-, and high-quality.

[5] See Lochner (2011) for an extensive review.

greater cross-class social connections, as measured by the extent of friendships across high and low SES groups, are a key factor for social mobility. Furthermore, we contribute to the literature on the returns to attending more selective HE institutions (Hoekstra, 2009; Zimmerman, 2014; Canaan and Mouganie, 2018; Anelli, 2020).[6] In line with our results, some studies show that access to better colleges can meaningfully foster the upward mobility of less privileged students (Dale and Krueger, 2002; Francis-Tan and Tannuri-Pianto, 2018; Andrews, Li and Lovenheim, 2016; Andrews, Imberman and Lovenheim, 2020; Black, Denning and Rothstein, 2023). To the best of our knowledge, our study is one of the first to examine the effect of attending a selective university on criminal behavior.

The remainder of the paper is organized as follows. Section 2 describes the public university that we study and its admission policy. Section 3 presents detailed information on main data sources and provides some key descriptive statistics. Section 4 presents our empirical strategy. In Section 5, we present our main results and discuss potential mechanisms. Section 6 concludes the paper. In addition, the Online Appendix contains information on other data sources and additional results.

## 2 Institutional Background

### *2.1 The Flagship University*

The *Universidade Federal de Pernambuco* (UFPE) is a flagship university in the Northeastern region of Brazil and one of the top ten public institutions in the country. It is considered a flagship institution because it is the one receiving the most support from the federal government in the state of Pernambuco, having the second largest budget among public universities in the Northeast. According to the Ministry of Education, this university has

[6] Worldwide, these returns are found to be explained by multiple mechanisms, such as selection into study programs (Hastings, Neilson and Zimmerman, 2013; Kirkeboen, Leuven and Mogstad, 2016), network formation (Zimmerman, 2019; Michelman, Price and Zimmerman, 2021; Jia and Li, 2021), human capital accumulation (Arteaga, 2018), and reputation (MacLeod et al., 2017; Sekhri, 2020).

had the highest evaluations in the North and Northeast since 1995.[7]

Like any other public institution in Brazil, it does not charge tuition fees. The right to free education at any level is guaranteed by the Constitution and enforced in public schools. The university currently has 31,235 undergraduate students, 9,148 graduate students, and 2,500 faculty members. It offers 105 undergraduate programs, with most of them taking at least four years to complete.

UFPE's main campus is located in the metropolitan area of Recife (MAR), and 84% of its applicants come from this area. MAR is the largest, second-richest, and second-most unequal metropolitan area in the Northern and Northeastern regions.[8] In 2016, it had more than four million people, and only 13% of the population between 16 and 24 years old were enrolled in tertiary education. From the population of college students, only 30% were enrolled in public institutions. Compared to other high-school graduates in Pernambuco, UFPE applicants are more likely to be white, come from a private high school, and have highly educated parents. Privileged students are even more predominant among those who are admitted (see Table A2, Online Appendix).

### *2.2 Admissions Process*

Since 1911, the law enforces HE institutions in Brazil to admit students using an exam, called *vestibular*. The purpose was to establish the minimum knowledge required for candidates to enter college. However, since the 1960s, the number of qualified candidates has been larger than the number of places available in public universities (de Mello e Souza, 1991). As a result, universities must admit students solely based on their rank in the *vestibular*.

UFPE admits about 95% of its undergraduate students through this exam, held only once a year.[9] The other 5% come from internal and external transfers to programs that are short

[7]Table A1 of the Online Appendix shows the ranking of HE institutions in Pernambuco; UFPE stands out for its quality and free tuition.

[8]Source: IBGE.

[9]In 2015, all programs at UFPE began to adopt the new national admission process (the Unified Selection System, SISU) to public universities in Brazil, ending institution-specific exams.

of junior and senior students. Some 68% of the applicants have recently graduated from high school, and only half are taking the exam for the first time. The minority consists of those who came from other institutions or undergraduate programs (12%), graduated from adult education programs (2.5%), or have not studied for a while (17.5%). In fact, anyone with a high school diploma or equivalent can apply to the university; the chances of being accepted depend uniquely on their test score.

The *vestibular* has two rounds. The first one assesses students' general knowledge and eliminates about 40% of the candidates.[10] In the second round, the remaining candidates are tested in Portuguese, a foreign language, and three subjects specifically required for the program of study. The final score is a weighted average of the first- and second-round scores.

The admission process requires candidates to choose their program of study when they apply. They are not admitted to the university as a whole, but to a particular undergraduate program offered by the institution. Also, they cannot apply to multiple programs in the same year. Each program offers a fixed number of seats and call applicants following their test score. After the *vestibular*, the admission committee fully discloses the ranking of candidates per program on its website and local newspapers. On average, only 10% of the applicants are admitted. However, some programs are more competitive than others. For instance, Law usually admits less than 5% of its applicants, whereas Mathematics admits almost 30%.

Using data from applicants in 2006 and 2007, Figure 1 shows how the relationship between the admission score and enrollment is discontinuous. Below the admission cutoff, standardized to zero, nobody can enroll in this university. Above the cutoff, every applicant receives the offer to enroll, and about 85% accept it. This discontinuity allows us to compare, for each program, the last students who received the offer and the first applicants who did not.

[10] Since 2010, the first round has been replaced by the National High School Exam (ENEM), which has a similar structure.

# 3 Data

Our data come from many different sources. The first is the UFPE admission committee (*Comissão para o Vestibular*, COVEST), which provides information on every applicant in 2006 and 2007. The second is UFPE's Academic Information System (*Sistema de Informações e Gestão Acadêmica*, SIGA), which has information on students' status (enrolled, graduated, or dismissed). The third is the Annual Social Information Report (*Relação Anual de Informações Sociais*, RAIS) from the Ministry of Labor, which contains data on every registered employee in Brazil. The fourth source is the universe of criminal and civil procedures collected from every Federal, State, and Labor court, which is publicly available as required by Brazilian law. Section A of the Online Appendix describes additional data sources.

### *3.1 Applications, Admission Score, and Socioeconomic Groups*

The COVEST data include the test scores from the first and second rounds of the *vestibular* and the final admission score. From 81,226 applicants, we restrict the sample to those who passed to the second round and applied to an oversubscribed program.[11] For the remaining 31,460 candidates, the final admission score is standardized using the admission cutoff — i.e., the admission score of the last student in the program each year — and their standard deviation by program and year.

These data also include the number of times each candidate did the admission exam in the past, motivation to enter the program, previous studies, and a long list of characteristics, such as age, gender, household income, and parents' education. With this information, we exclude candidates who were over 30 years old or already attending an HE institution, losing 34% of the observations. This exclusion is motivated by the fact that criminal activity declines with age (Sampson and Laub, 2005), and HE students had already been exposed to

[11] About 13 programs per year are excluded because the number of places available was greater than the number of applicants remaining in the second round.

a college environment.

Following a definition from the Ministry of Education, we classify as 'low-income' those that report a monthly household income below 1,000 BRL, which corresponds to 5,500 USD a year. In 2016, about 54% of households in Brazil were below this income level. Also, we classify as 'high-income' those with monthly household income above 2,000 BRL (11,000 USD/year). In the whole country, only 21% of the households had income above this threshold in 2016. As an alternative, we also group applicants based on parents' education (having a college degree or not). After excluding observations with missing socioeconomic information, the final sample has 20,620 observations.[12]

### *3.2 College Enrollment and Status*

SIGA provides detailed information on all the students enrolled in 2002-2014, regardless of when they enter and leave the institution. With these data, we verify whether admitted students enrolled in the university in the same year that they originally applied. This information is used to measure compliance to the treatment. We also check whether and when a student graduated from this institution.

### *3.3 Employment, Earnings, and Educational Attainment*

In Brazil, every registered firm is legally required to annually report every worker employed in the previous year, with information on salary, number of months worked, and education level. This information is available on RAIS. Using students' social security numbers (*Cadastro de Pessoa Física*, CPF), we match the two previous data sources with RAIS to obtain their earnings, occupation, and years of schooling for every year from 2002 to 2017. From the 20,620 observations in our final sample, we find 84% of them in at least one year of RAIS.

From RAIS, we calculate individual earnings as the sum of all salaries received within 12 months, deflated to December 2017 using the Extended Consumer Price Index (IPCA). For

[12] As explained in Section 4, we also exclude the last student admitted per year and program, whose admission score equals the admission cutoff.

each year, individuals are considered formally employed if they are found on RAIS, regardless of how many weeks and hours they worked.[13] For each employed worker, we also calculate their experience (number of months employed since their first formal occupation) and tenure (number of months working for their current employer).

The estimated effects of admission on earnings are restricted to the sample of applicants who are found to be formally employed in the future. Accordingly, we do not estimate the effect on students' total income, which would also include earnings from informal jobs and self-employment. According to the Brazilian National Household Survey (*Pesquisa Nacional por Amostra de Domicílios*, PNAD), this restriction implies that we potentially ignore the earnings of 24% of the applicants.[14] However, we show in Section 5.2.A that this restriction is not a concern because the share of students formally employed is balanced at the admission cutoff and our main results persist for the subsample of formal workers. Another concern regarding income is whether formal employees complement their salaries with informal and entrepreneurial earnings. According to PNAD, less than 3% of the formal employees in Pernambuco, who hold a high school degree, have a second job as an informal employee or self-employed.

For educational attainment, the analysis is also restricted to students who were formally employed. This analysis is considered valid as long as formal employment is balanced at the admission cutoff (see Section 5.2.A). A second concern, though, is whether the years of schooling on RAIS is accurately reported. Compared to the accurate information available on SIGA, we find that 96% of the UFPE graduates report to hold a college degree on RAIS.

[13] Workers that are not found on RAIS are not necessarily unemployed. They can also be unregistered. In either case, we consider their absence from the records as a sign of underemployment.

[14] If we only consider workers in the state of Pernambuco, who are 25 years or older, and who attended at least one year of HE, about 5% of them are informal employees, 7% are informally self-employed, 12% own a formal business, and 9% are unemployed.

### *3.4 Legal Prosecution*

Data on first-instance criminal and civil prosecutions are publicly available and compiled by a private company named Kurier. This company offers data analytics services in the judicial area, having large firms as its main clients. Every day, its server downloads all the reports publicly disclosed by any Federal, State, and Labor court in Brazil. Using machine learning tools, the company extracts key data, such as plaintiffs, defendants, attorneys, judges, compensatory and punitive damages, and appeals, from PDF files and stores them in its database.

Since this data collection process started effectively in late 2008, we obtained all the lawsuits between 2009 and 2017. Then we match the lists of defendants and former UFPE applicants using their full names. If an applicant's name perfectly matches a defendant's name, we assume that he or she has a civil or criminal record. Otherwise, their record is clean. On the one hand, this method underestimates the legal history of candidates who changed their names. On the other hand, it overestimates the history of those with common names. Fortunately, at least among UFPE applicants, 99% of the names are unique. Moreover, in our empirical strategy, the mismeasurement caused by common and incorrect names should equally affect treated and untreated groups close to the admission cutoff, so the estimated effect remains unbiased. Still, estimations of criminal charges at the intensive margin (i.e., number of prosecutions) are too sensitive to outliers. Thus, as a precaution, we only estimate the effect at the extensive margin (i.e., being or not being prosecuted).

For the construction of criminal outcomes, we only consider whether the applicant was prosecuted or not. We do not take the court decisions into account because they are potentially affected by access to better lawyers (see Agan, Freedman and Owens, 2021). Then we classify criminal cases into five non-exclusive groups: violent, property, against the public interest, traffic-related, and unclassified. Violent crime comprises homicides, personal injuries, threats, sexual assaults, and gun use. They can be either domestic or non-domestic. Property crime includes robberies, thefts, trespassing, and property rights violations. Crime against the public interest includes all drug-related crimes, frauds, tax evasion, and crimes against public officials. Traffic-related crime comprises criminal violations such as DUI, reckless driving, and driving without a license. The last category includes all criminal violations without accurate information on the subject matter. Regarding civil cases, we identify three categories: divorce trials, collection lawsuits (for non-payment of debt), and other civil cases.

### *3.5 Descriptive Statistics*

Table 1 exhibits the descriptive statistics for outcomes and other covariates used in this study. The simple comparison shows that admitted candidates are half as likely to be criminally prosecuted as the non-admitted within ten years following the college application. After these ten years, their expected earnings are nearly 50% higher than in the other group.

In terms of educational attainment, almost 63% of the non-admitted candidates hold a college degree in the future. Among the admitted, this rate jumps to 79%. These numbers reveal that UFPE is far from being the only HE option the non-admitted applicants have, and a considerable fraction of admitted students does not graduate from college. Indeed, only 64.5% of the admitted students graduate from UFPE, while 14% graduate from another institution. For the non-admitted (in a given year), the probability of graduating from UFPE is about 15%.

The admission process at the flagship university is so competitive that admitted students report, on average, at least two previous *vestibular* attempts, and 60% of them attend preparatory programs. Accordingly, admitted and non-admitted groups are quite different in terms of socioeconomic background. Compared to the non-admitted, admitted candidates are 6.7 p.p. more likely to report high income, 6.9 p.p. to have a parent with a college degree, and 2.1 p.p. to come from a private high school. Among the reasons to apply to this university, 37% of the candidates say because it is free. The second most common reason, reported by 27.4%, is the institution's prestige.

# 4 Empirical Strategy

Estimating credible effects of attending a highly selective university is difficult due to many sources of selection bias. Students' observed and unobserved traits are correlated with this opportunity. To undermine the confounding factors, we apply an RDD at the admission cutoff (Hahn, Todd and Van der Klaauw, 2001; Imbens and Lemieux, 2008). Since admission is strictly based on a test score, taken only once a year, the last student admitted to the university is very similar to the first candidate left out. The only difference between them is the right to attend the flagship institution.

However, the candidates do not apply to the university as a whole. Instead, they apply to one (and only one) of its undergraduate programs. Given that each program has a different cutoff every year, we follow Pop-Eleches and Urquiola (2013) and Zimmerman (2019) and stack the sample across years and programs. Then we standardize the admission scores within year-program so that each cutoff is equal to zero. According to Cattaneo et al. (2016), this standardizing-and-pooling approach yields consistent estimates for the local average treatment effect (LATE).

Formally, let $x_{ikt}$ be the admission score of applicant $i$ who applies to program $k$ in year $t$, and $\underline{x}_{kt}$ be the score of the last student joining this program that year. If $x_{ikt} \geq \underline{x}_{kt}$, then the applicant may enroll in the university. But if $x_{ikt} < \underline{x}_{kt}$, then the applicant cannot, under any circumstances, start the program they applied to. Let $y_{ikt}^{T}$ be the criminal record in year $T$ of applicant $i$, who applies to program $k$ in year $t$, where $T > t$. This variable may also represent any other outcome, such as the applicant's salary and educational attainment in the future. Then the LATE of admission to a applicant's criminal record in year $T$ is given by the following sharp regression discontinuity (SRD) estimand:

$$\tau_{SRD}^{T} = \lim_{x \downarrow \underline{x}} E\left(y_{ikt}^{T} \middle| x_{ikt} \geq \underline{x}_{kt}\right) - \lim_{x \uparrow \underline{x}} E\left(y_{ikt}^{T} \middle| x_{ikt} < \underline{x}_{kt}\right). \tag{1}$$

Since not every admitted candidate enrolls in the university, the LATE of enrollment in the flagship university is given by the following fuzzy regression discontinuity (FRD) estimand:

$$\tau_{FRD}^{T} = \frac{\tau_{SRD}^{T}}{\lim_{x \downarrow \underline{x}} \Pr\left(z_{ikt} = 1 | x_{ikt} \geq \underline{x}_{kt}\right) - \lim_{x \uparrow \underline{x}} \Pr\left(z_{ikt} = 1 | x_{ikt} < \underline{x}_{kt}\right)}, \tag{2}$$

where $z_{ikt}$ is equal to one if applicant $i$ enrolls in program $k$ in year $t$ and zero otherwise, and Pr(.) is a probability function. As shown in Figure 1, the probability of enrollment below the cutoff, $\Pr\left(z_{ikt} = 1 | x_{ikt} < \underline{x}_{kt}\right)$, is zero. Above the cutoff, the probability is around 85%.

Identifying these LATEs relies on the fact that applicants around the cutoff are similar in every aspect. Still, a few issues, if existed, could violate this condition. First, the performance in the admission exam might depend on how far the applicants are from the cutoff. Second, non-admitted applicants could take the exam multiple times until they pass. Third, the university could apply a second admission criterion based on soft information. Fourth, other institutions could use the admission score for the flagship as an admission criterion, making admitted candidates more likely to reject the flagship offer than the non-admitted. Fortunately, none of these issues applies to our setting. All the applicants take the exam at the same time, nobody can retake it in the same year, and the cutoff is unknown until all the scores are released. Also, for any institution, applying an admission criterion other than its own admission score is against the law. The admission process for HE in Brazil is transparent, requiring all institutions to publicly disclose the ranking of candidates.

Despite the favorable institutional framework, the sample must still satisfy local continuity assumptions to validate the RDD. Accordingly, we apply the Cattaneo, Jansson and Ma (2020) version of the density continuity test, originally proposed by McCrary (2008), and find no evidence for discontinuity in the density of observations at the cutoff (see Figure A1, Online Appendix). Moreover, no covariate measured at the time of the exam is significantly discontinuous at the cutoff (Table A3, Online Appendix). The same continuity conditions also hold for the subsamples that we study — i.e., low- and high-income groups. While interpreting the effects on low- and high-income applicants, it also helps that their enrollment rates are very similar (see Figure 1).

Another potential issue with our approach is the endogeneity of the admission cutoff. According to de Chaisemartin and Behaghel (2020), when the cutoff is defined by the last students accepting the offer, the compliance to the offer becomes higher in the treated group than in the untreated one. To re-balance the compliance rate, they point out that excluding the last student enrolled in each program from the sample would be enough. Accordingly, for each program cohort, we exclude the applicant whose admission score, $x_{ikt}$, is equal to the admission cutoff, $\underline{x}_{kt}$.[15]

To estimate LATEs (1) and (2), we apply locally weighted regressions (LWR) with a triangular kernel function and a first-degree polynomial. Following Calonico, Cattaneo and Titiunik (2014), we select the bandwidth using a minimum square error (MSE) procedure and adjust our estimates for the large-bandwidth bias. Since we use two cohorts of applicants, one may appear twice in our sample. For this reason, we cluster the standard errors at the candidate level.

Although Cattaneo et al. (2016) state that the standardizing-and-pooling approach is consistent, they also argue that settings like ours, including many program cohorts, can be used to consistently examine heterogeneous effects. Therefore, we further split the sample into types of programs to verify some of the potential mechanisms. Unfortunately, given our sample size, we cannot split the sample of high- and low-income students into more than three groups without compromising the statistical power of our estimates. For small samples, Calonico, Cattaneo and Titiunik's (2014) estimator does not always work because it requires a minimum number of observations within the bandwidth. When it does, estimates are often noisy, which leads to an attenuation bias in the average effect.

To narrow the list of potential mechanisms to viable candidates, we also gradually include control variables in our regressions, as proposed by Calonico et al. (2019). Since some of these covariates can be considered "bad" controls, as defined by Angrist and Pischke (2009), the purpose of the exercise is not pin down the mechanism through which admission affects

[15]The non-exclusion of these candidates does not change our findings. Results are available upon request.

earnings. Instead, it is only intended to eliminate potential channels for which inclusion in the model do not change the LATE.

## 5 Results

We start this section by presenting our main finding: admission to a tuition-free flagship university reduces criminal charges among admitted students. Then we investigate possible mechanisms for this effect.

### *5.1 Effect of Admission on Criminal Prosecution*

Figure 2 displays the relationship between the admission score of applicants and the probability of a criminal charge within ten years following the application. In the left-hand graph, we observe that being admitted to the flagship university reduces this probability by 2.5 p.p. Compared to the baseline probability (3.6%), which is the predicted value to the left of the cutoff, the effect represents a 69% reduction. The middle and right-hand graphs indicate that the effect on low-income students drives most of the average effect. The reason is their baseline rate (5.7%) is five times as high as the rate for high-income students (1.1%), so they should be more sensitive to admission. If admitted, their probability of being criminally charged declines by 4.3 p.p. (or 77%). For high-income students, the effect is at 0.9 p.p. (or 81%), which is statistically insignificant.

In addition to the admission effect, column (1) of Table 2 presents the FRD estimate for the effect of enrollment. Panel A shows that, on average, enrollment reduces the probability of prosecution by almost 3 p.p. For the low-income group (in panel B), the reduction is over 5 p.p., while for the high-income group (in panel C) is close to 1 p.p. A similar difference between groups is found if we split students based on parental education. Table A4 of the Online Appendix shows that the effect is large and significant if neither parent holds a college degree, and small and insignificant if either parent does. The difference between income groups is also observed when we look at male and female applicants separately, though the effect on men is larger than on women (Tables A5 and A6, Online Appendix).

Table 2 also shows the results separated by type of crime, from columns (2) to (6). For all students (in panel A), the effect on violent crimes is slightly higher than the others, but we also observe significant reductions in property crimes and violations against the public interest. Except for traffic-related crimes, all forms of violations decline by at least 65% from the baseline rate. For low-income students (in panel B), though, the effect of admission on violent felonies (3.2 p.p.) is relatively higher, representing a reduction of 89% in their likelihood of committing this type of crime. For other felonies, the effect is lower than 70% and insignificant. Despite the lack of statistical power, we also observe in panel C that admission significantly reduces the probability of high-income students being prosecuted for traffic-related crimes and crimes against the public interest. These two forms of crime are the main reasons high-income applicants are prosecuted.

The estimates shown in Figure 2 and Table 2 were obtained using a MSE-optimal bandwidth. However, our findings are robust if we apply a range of smaller and larger bandwidths (Figure A2, Online Appendix). They are also robust if we use different RDD estimators. Table A7 of the Online Appendix presents the estimates obtained from LWR with second-degree polynomials and from comparing applicants based on ordinal rank per program cohort instead of admission scores. Table A8 of the Online Appendix presents the estimates controlling for program cohort fixed effects. None of these alternative specifications yields considerably different results.

Another concern is whether the effect is caused by the frustration of being nearly admitted or the gratitude of barely making it (or both). That is, candidates who are just above or below the admission cutoff would behave differently than the rest. To mitigate this concern, we reestimate the effects excluding observations that are too close to the cutoff. The resulting estimates are similar to the main results (Table A9, Online Appendix).

To verify the timing of the effects, panel (a) of Figure 3 presents the estimates for each year after the college application. Panel (b) presents the effect on the cumulative probability of being prosecuted over time. These graphs show that the reduction in the probability starts four years after the application, which is when students should begin their transition from college to the labor market. This effect persists for at least 12 years after the application.

In summary, low-income applicants are more likely to be criminally prosecuted in the next ten years than wealthier applicants. However, enrollment in a top-quality institution more than halves this likelihood, mostly for violent crimes. All told, admission to the flagship university changes a student's life in many ways. Below, we explore some potential mechanisms.

### *5.2 Potential Mechanisms*

In this section, we explore some potential mechanisms that might explain the effect of admission on criminal charges, such as unemployment, earnings, and educational attainment. However, most of the variables examined below come from RAIS, so they are only observed for applicants who have been formally employment. Given this sample restriction, we must first show that the probability of being a formal employee is not affected by admission to the flagship university. In other words, formal employment is balanced at the admission cutoff. It is also worth mentioning that this restriction does not change our main results (see Table A10, Online Appendix).

#### *5.2.A Formal Employment*

Figure 4 presents the effect of admission on the probability of having a registered job each year after college application. Each point in these graphs comes from a separate SRD. They show that, for almost every year, formal employment is barely affected. Exceptions are for low-income students in years four and five, when they are finishing their studies and entering the labor market, and for high-income students in year seven. However, the effects disappear later. By year ten, formal employment becomes balanced around the admission cutoff. Furthermore, work experience and job tenure are not significantly affected by admission (see

Figure A3, Online Appendix). Therefore, we can confidently compare applicants who were formally employed ten years later in terms of earnings and educational attainment.

Despite the balance in formal employment in year ten, transient unemployment and informality might explain the effect on criminal charges (Dix-Carneiro, Soares and Ulyssea, 2018; Britto, Pinotti and Sampaio, 2022). Namely, admission may reduce criminal behavior by increasing the time students spend in formal occupations, taking time off from other activities and raising the opportunity cost of committing crimes. According to Figure 4, though, the effect of admission on low-income students' employment is negative, reducing the opportunity cost of crime among admitted students. If anything, the effect on formal employment goes against the potential mechanism. Moreover, Figure 3 shows that the effect on criminal charges also appears in years when the effect on employment is null. The results are similar if we measure formal employment as the share of days worked per year (Figure A4, Online Appendix).

#### *5.2.B Type of Program*

According to Duryea et al. (2023), admission to the flagship university has significant effects on educational attainment and earnings. Hence, we cannot rule out these potential mechanisms without further analysis. To investigate their relationship with the effect on criminal prosecution, we follow Cattaneo et al.'s (2016) approach and split the sample by type of program.

In Table 3, we separate the programs in two ways, based on the share of low-income students among admitted applicants, in columns (1) to (3), and the share of admitted students from private high schools, in columns (4) to (6). Using both variables, programs are split into quartiles, aggregating the quartiles with the two smallest sample sizes in each income group. Given our limited sample size, we cannot split the samples of high- and low-income applicants into more than three parts without compromising the statistical power.

Results in panel A show that the effect on criminal prosecution of low-income students is large and significant only in programs with a low share of low-income students — see column (1) — or with a high share of student from private high schools — see column (6). To facilitate our narrative, we refer to these programs as 'high' SES programs. In other ('low' SES) programs, the effect is small and insignificant, even though the baseline criminal rate is still large.

These findings indicate that the effect on low-income students is not driven by the composition of student in programs with potentially higher impact. Instead, the effect is larger in programs where low-income students are underrepresented. Below, we examine other effects that these programs might have on low-income students. Unfortunately, our empirical setting does not allow us to explore whether the effect on criminal charges is caused by the interaction with high-SES students or by institutional differences between programs (e.g., difference in instructors, content, buildings, and classrooms).

*5.2.C Earnings*

Despite the null effect on formal employment, it could be that attending the flagship university pays a higher wage premium than the alternatives, including the alternative of not attending college (Dale and Krueger, 2002; Anelli, 2020). The higher earnings could, in turn, affect students' criminal behavior (Grogger, 1998).

Table 4 presents the estimated effect of admission on log earnings ten years after application, using the same sub-samples as in Table 3. Column (1) shows that admission increases future earnings by 25% in the low-income group. For the high-income group, the average effect is small and insignificant.

Columns (4) and (5) indicate that the effect on the earnings of low-income students is large and significant in low SES programs. In high SES programs — columns (2) and (7) — the effect on earnings is small and insignificant. By comparing the results in Tables 3 and 4, we find that the effects on future earnings and criminal prosecution of low-income students do not match. While the effect on criminal charges is higher in high SES programs, the effect on earnings is higher in low SES programs. Therefore, the effect of admission on criminal charges seems unrelated to earnings.

### *5.2.D Educational Attainment*

Although the effect on criminal charges appears to be unrelated to earnings, it could also be the case that education itself affects students' behavior. For instance, admitted students might commit fewer crimes due to the incapacitation created by college enrollment (Bell, Costa and Machin, 2016, 2022). In that case, any college degree would have a similar effect.

In Table 5, we present the estimated effects of admission to the flagship university on college attendance and graduation from some HE institution. If admitted, students are about 35 p.p. more likely to graduate from the flagship university within ten years, with a slightly higher effect among low-income students — see column (1). The effect of admission on graduation is not larger because some programs are too difficult to complete and have low retention. On average, more than 20% of the enrolled students do not finish their degree. Also, non-admitted candidates often reapply to the flagship university in the following years. As a result, the admission effect on enrollment of high- and low-income students drops from 85 p.p. in the first year to less than 60 p.p. later (Figure A5, Online Appendix), reducing the gap between admitted and non-admitted students.

Furthermore, non-admitted applicants appear to enroll in other HE institutions. Column (2) of Table 5 shows that they are only 5.2 p.p. less likely to go to college and 2.8 p.p. less likely to graduate from some HE institution. For these two outcomes, the effects are larger for the low-income group than for the high-income one. Nevertheless, they are not large enough to explain the changes in criminal prosecution. Columns (4)-(7) confirm that the effect on criminal prosecution does not change after we control for college attendance and graduation.

Another approach to verify whether educational attainment explains the effect on criminal prosecution is to estimate the effect for high and low SES programs. The results in panel A of Table 6 reveal that the effect on college attendance is higher and significant for low-income students enrolled in low SES programs — in columns (3) and (4). For other students, the effect is smaller and insignificant. Since the effect on criminal prosecution is concentrated among low-income students in high SES programs (see Table 3), it does not seem to be correlated with the effect on attendance. Also, the effects on graduation from the flagship university or any other institution are similar between high and low SES programs (Tables A11 and A12, Online Appendix), so uncorrelated with the effect on crime.

*5.2.E Institutional Quality*

Despite the small effect on educational attainment, a more meaningful difference between admitted and non-admitted applicants is in the quality of their HE education. To verify where applicants obtain their college degree in the future, we use a web search platform, called *Escavador*, specialized in finding up-to-date information of individuals in Brazil. On this platform, we were able to find 36% of the applicants who later hold an academic degree. We understand that this sample might be biased, so the following results should be taken with a grain of salt. Fortunately, it plays in our favor that admission does not significantly affect the probability of finding applicants on the platform (Table A13, Online Appendix). Details on this data source are in Section A of the Online Appendix.

With the information obtained from *Escavador* combined with the institutional quality rated by the Ministry of Education, we create dummy variables indicating whether the applicant graduates from a high-quality institution and whether they graduate from a high-quality program. Column (1) of Table 7 confirms that students admitted to the flagship university are 39 p.p. (or 84%) more likely to hold a degree from a high-quality college than non-admitted candidates. The result is similar for both low- and high-income applicants, in panels B and C, and for those who hold a college degree, in column (4).

As we split the sample into low and high SES programs — i.e., high and low share of low-income students, respectively —, we observe that the admission effect on quality is slightly larger for students applying to high SES programs (or low share of low-income students). For low-income students, though, the difference is more salient. In low SES programs, low-income students are 22 p.p. more likely to graduate from a high-quality college. In high SES programs, they are 71 p.p. more likely to graduate from a high-quality college. This difference is consistent with the larger reduction in criminal charges in high SES programs.

#### *5.2.F Other Results*

Another reason for the reduction in criminal prosecution is that individuals could be less distressed if they attend the tuition-free institution. To test this hypothesis, we estimate the admission effects on the probability of facing three legal events: a divorce trial, a collection lawsuit, and other civil lawsuits. Table 8 presents the estimated effect on the probability of litigation within ten years after the application. The effects are neither large nor significant. If anything, admitted students are more likely to be sued in a civil case. Results are similar if we split the samples into high and low SES programs (Table A14, Online Appendix).

One may also argue that the effect on low-income students does not necessarily represent a reduction in criminal behavior. By interacting with high-income peers, these students might learn how to avoid legal prosecution after committing crime. If this hypothesis were true, we should also observe the learning mechanism in civil lawsuits. However, we do not observe a reduction in the probability of being sued among low-income students. Furthermore, we reestimate the effects on criminal prosecution excluding candidates applying to law school, where we assume the learning mechanism is stronger. The results indicate that the effect on this sample is slightly larger (Table A15, Online Appendix).

The last hypothesis that we test regards the probability of migrating after applying to the university. In the future, better job opportunities may encourage admitted students to move away from the criminal environment in which they grew up. However, the estimated effect on migration is insignificant for at least 12 years after application (Figure A6, Online Appendix).

## 6 Conclusion

In this paper, we examine the relationship of attending a top-quality, tuition-free university in Northeast Brazil — one of the world's most violent regions — on the criminal prosecution of students. To do so, we exploit a rich database with the universe of criminal and civil prosecutions in Brazil, combined with the fact that admission to the university presents a sharp discontinuity. This discontinuity allows us to identify causal effects by comparing applicants just above and below the admission cutoff across many programs of study.

We find that crossing the admission threshold reduces low-income students' probability of criminal prosecution by 77% (or 4.3 p.p.). Most of this effect occurs through the reduction in violent crimes. Furthermore, the effect on low-income students is found to be concentrated in high SES programs. Thus, the opportunity to attend a program with a prevalent presence of students from a distinct socioeconomic group appears to reduce criminal charges in the future. We also present evidence that the crime reduction seems related to observed institutional quality.

In the context of our study, the effect on crime reduction does not seem motivated by economic gains. The reason is the effects of admission to the flagship university on educational attainment and formal employment are not large enough to explain the reduction in criminal charges. Furthermore, only low-income students in low SES programs experience significant increases in future earnings. Yet these students do not present a significant reduction in criminal behavior. Therefore, the crime reduction appears to have more social than economic drivers.

Overall, this paper underscores the role of HE in reducing crime and violence in emerging countries. Given the enormous quality gap in basic education between socioeconomic groups, the high-quality public universities in Brazil provide a unique opportunity for high-achieving students from different backgrounds to attend a common learning environment, which, in turn, has lasting effects on criminal behavior. Altogether this implies that current policies facilitating access of underrepresented students to selective programs may have even larger effects by encouraging more inter-group interactions through activities such study groups, and extra-curricular activities. Moreover, these interventions may yield social returns that are broader than fostering income mobility.

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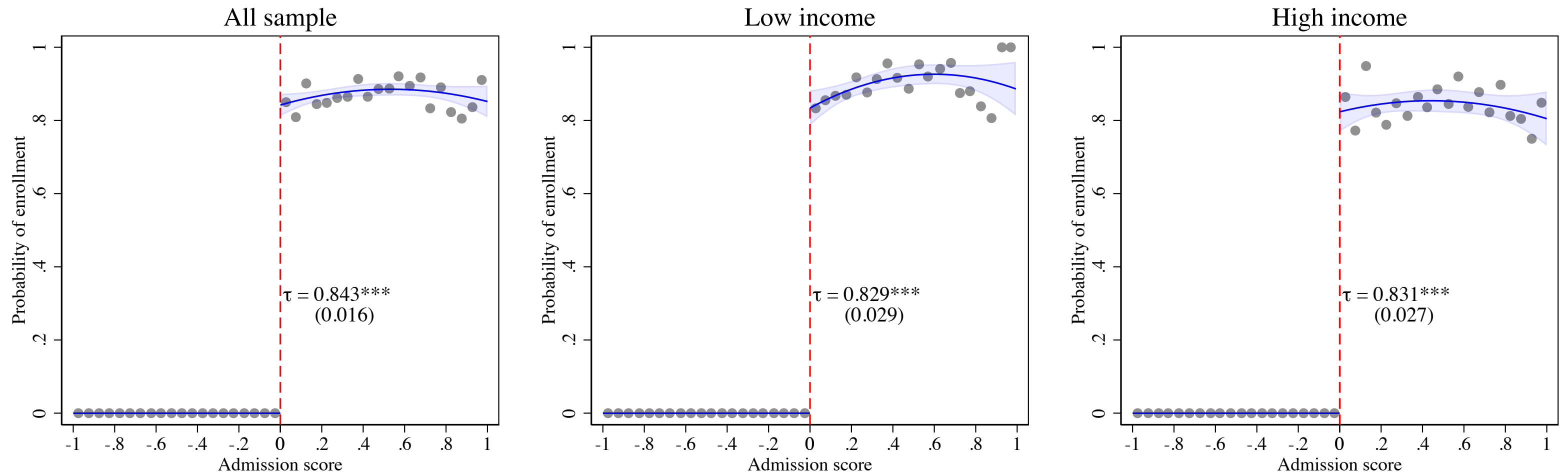
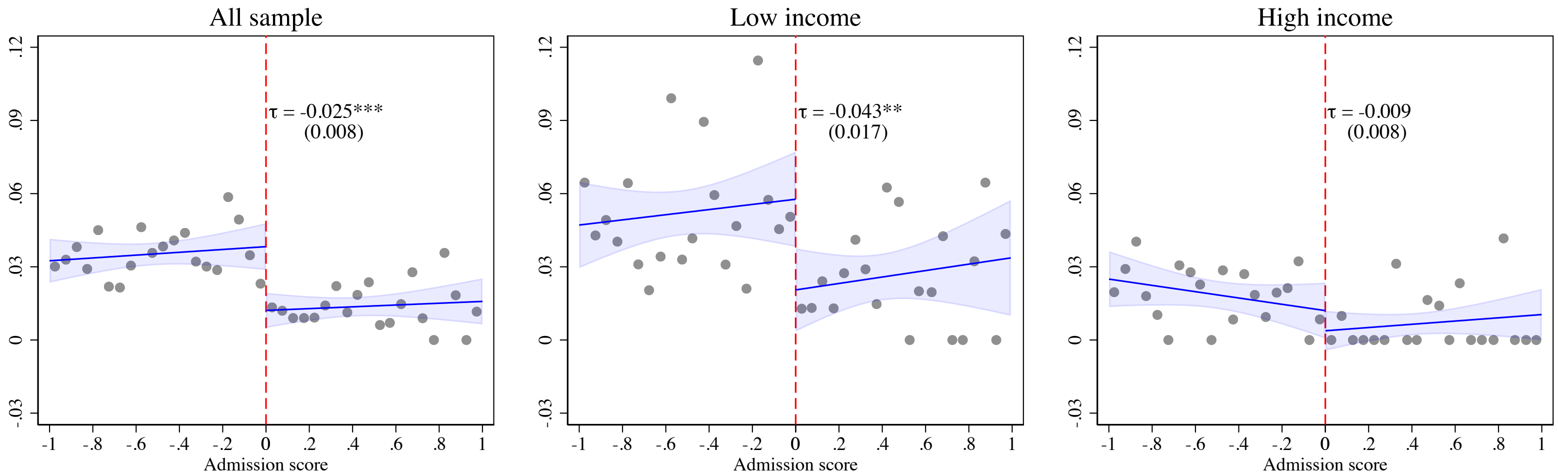
**Figure 1:** Relationship Between Admission Score and Enrollment at the Flagship University




The admission score (x-axis) is standardized using the admission cutoff and the standard deviation of all applicants that passed to the second round by program and year. The dependent variable (y-axis) is equal to one if the applicant enrolled in the flagship university in the same year as the admission exam and zero otherwise. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Grey dots represent mean values within bins of 0.05 standard deviations in the admission score. Nonparametric functions are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence interval at 95% level. $\tau$ is the sharp regression discontinuity estimate, with robust standard errors clustered at the applicant level in parenthesis. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

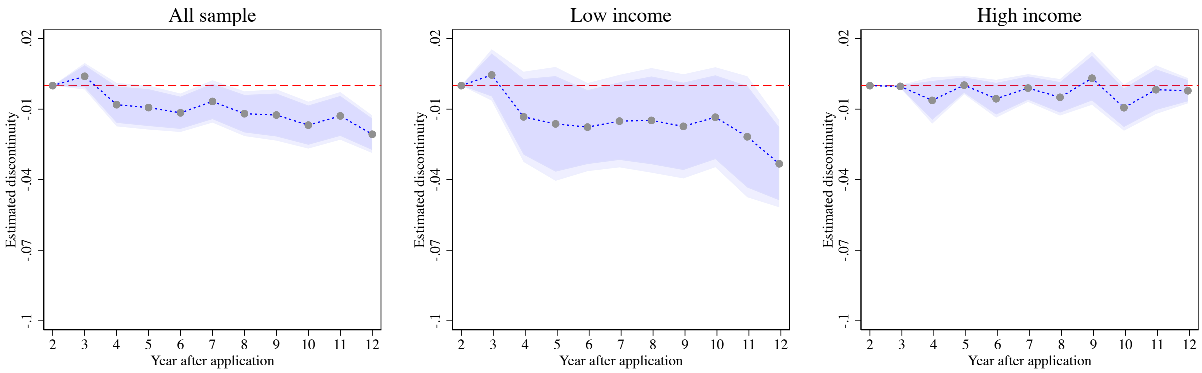
**Figure 2:** Relationship Between Admission Score and the Probability of Criminal Prosecution in the Following Decade



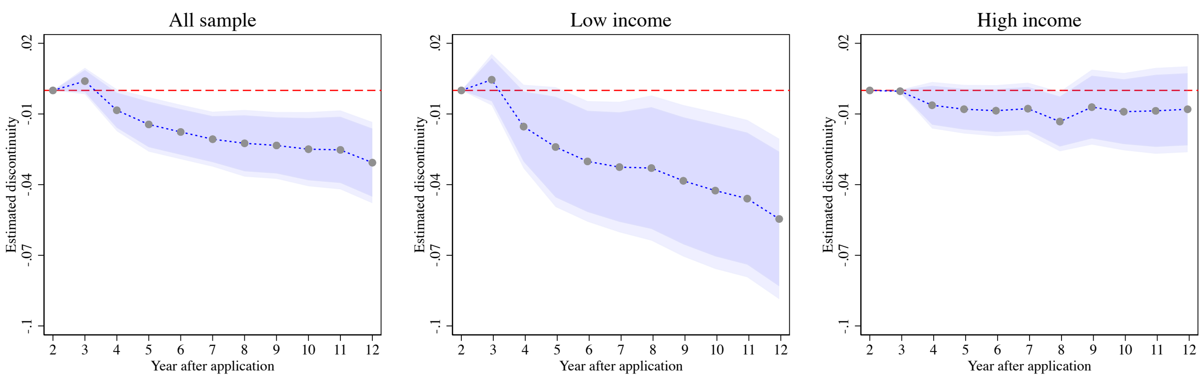

This figure presents the relationship between the admission score and the probability of criminal prosecution. The admission score (x-axis) is standardized using the admission cutoff and the standard deviation of all applicants that passed to the second round by program and year. The dependent variable (y-axis) is equal to one if the applicant was criminally prosecuted within ten years following the application to the university and zero otherwise. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Grey dots represent mean values within bins of 0.05 standard deviations in the admission score. Nonparametric functions are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence interval at 95% level. $\tau$ is the sharp regression discontinuity estimate, with robust standard errors clustered at the applicant level in parenthesis. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Figure 3:** Effect of Admission on Criminal Prosecution by Year After Applying to the Flagship University

**(a)** Effect on Probability per Year

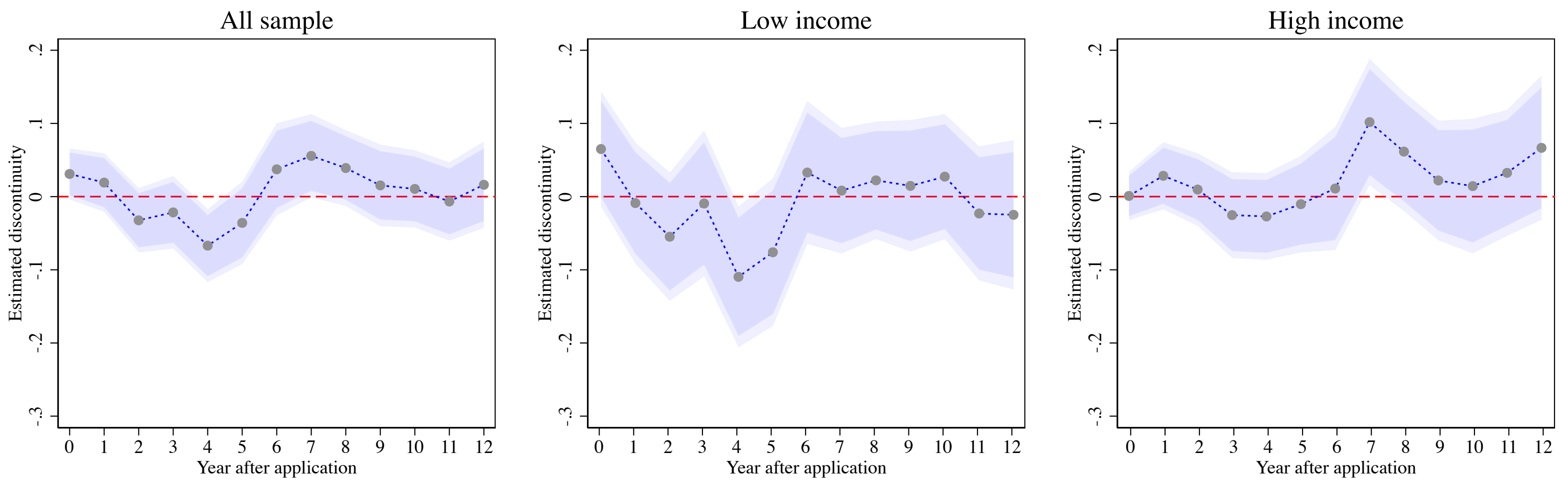



**(b)** Effect on Cumulative Probability




This figure presents the SRD estimates for probability of criminal prosecution (y-axis) in each year after applying to the university (x-axis). For each year in panel (a), the dependent variable is equal to one if the applicant was criminally prosecuted that year and zero otherwise. For each year in panel (b), the dependent variable is equal to one if the applicant was criminally prosecuted that year or before and zero otherwise. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence intervals at 90% (darker) and 95% (lighter) levels. Standard errors are clustered at the applicant level.

**Figure 4:** Effect of Admission on Formal Employment by Year After Applying to the Flagship University






This figure presents the SRD estimates for employment (y-axis) in each year after applying to the university (x-axis). For each year, the dependent variable is equal to one if the applicant was formally employed for at least a month and zero otherwise. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence intervals at 90% (darker) and 95% (lighter) levels. Standard errors are clustered at the applicant level.

**Table 1:** Descriptive Statistics

| | All | | Admitted | | Non-admitted | |
|---|---|---|---|---|---|---|
| | mean | s.d. | mean | s.d. | mean | s.d. |
| Criminally prosecuted* | 0.029 | 0.167 | 0.015 | 0.122 | 0.032 | 0.176 |
| Standardized admission score | -0.905 | 1.127 | 0.714 | 0.631 | -1.336 | 0.786 |
| Enrolled after admission (same year) | 0.182 | 0.386 | 0.863 | 0.344 | 0.000 | 0.000 |
| Attended college* | 0.807 | 0.394 | 0.891 | 0.311 | 0.784 | 0.411 |
| Has a college degree* | 0.662 | 0.473 | 0.787 | 0.409 | 0.628 | 0.483 |
| Graduated from UFPE* | 0.257 | 0.437 | 0.645 | 0.479 | 0.154 | 0.361 |
| Formally employed** | 0.642 | 0.480 | 0.684 | 0.465 | 0.630 | 0.483 |
| Log earnings*** | 10.43 | 0.983 | 10.73 | 0.925 | 10.34 | 0.982 |
| Migration*** | 0.183 | 0.386 | 0.202 | 0.401 | 0.177 | 0.382 |
| Female | 0.578 | 0.494 | 0.541 | 0.498 | 0.588 | 0.492 |
| Age | 19.95 | 2.570 | 20.09 | 2.457 | 19.92 | 2.598 |
| Number of previous attempts | 1.896 | 0.965 | 2.123 | 0.969 | 1.836 | 0.955 |
| Attended preparatory program | 0.503 | 0.500 | 0.602 | 0.490 | 0.476 | 0.499 |
| Attended private high schools | 0.697 | 0.459 | 0.714 | 0.452 | 0.693 | 0.461 |
| *Income brackets* | | | | | | |
| Low income (< 1,000 BRL/month) | 0.382 | 0.486 | 0.328 | 0.470 | 0.396 | 0.489 |
| High income (> 2,000 BRL/month) | 0.333 | 0.471 | 0.386 | 0.487 | 0.319 | 0.466 |
| One parent has college degree | 0.452 | 0.498 | 0.507 | 0.500 | 0.438 | 0.496 |
| One parent is underemployed | 0.199 | 0.399 | 0.176 | 0.381 | 0.205 | 0.403 |
| One parent is an entrepreneur | 0.206 | 0.404 | 0.226 | 0.418 | 0.200 | 0.400 |
| Living in MAR | 0.885 | 0.319 | 0.922 | 0.268 | 0.875 | 0.331 |
| *Main reason to choose program of study* | | | | | | |
| Career prestige | 0.028 | 0.166 | 0.016 | 0.125 | 0.031 | 0.175 |
| Quality of the program | 0.086 | 0.280 | 0.087 | 0.282 | 0.085 | 0.279 |
| Personal self-fulfilment | 0.544 | 0.498 | 0.577 | 0.494 | 0.536 | 0.499 |
| Other reasons | 0.342 | 0.474 | 0.320 | 0.467 | 0.347 | 0.476 |
| *Main reason to apply to UFPE* | | | | | | |
| No tuition fees | 0.371 | 0.483 | 0.350 | 0.477 | 0.376 | 0.484 |
| University's prestige | 0.274 | 0.446 | 0.297 | 0.457 | 0.268 | 0.443 |
| Other reasons | 0.356 | 0.479 | 0.353 | 0.478 | 0.356 | 0.479 |
| Number of observations | 20,620 | | 4,338 | | 16,282 | |

This table presents the mean and standard deviation (s.d.) of dependent variables and covariates used in this study. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. The sample is also split between applicants that were 'admitted' and 'non-admitted' after the admission exam. * within ten years after applying to the university. ** in the tenth year after applying to the university. *** if employed in the tenth year after applying to the university.

**Table 2:** Effects of Admission and Enrollment on the Type of Crime

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.025*** | -0.016*** | -0.013*** | -0.012** | -0.006 | -0.014** |
| | (0.008) | (0.006) | (0.005) | (0.005) | (0.004) | (0.006) |
| Enrollment | -0.029*** | -0.019*** | -0.015*** | -0.015** | -0.007 | -0.016** |
| | (0.009) | (0.007) | (0.005) | (0.006) | (0.005) | (0.007) |
| *Baseline mean* | 0.036 | 0.022 | 0.017 | 0.017 | 0.011 | 0.021 |
| *N. of observations* | 20,620 | 20,620 | 20,620 | 20,620 | 20,620 | 20,620 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.043** | -0.032** | -0.017 | -0.015 | -0.007 | -0.015 |
| | (0.017) | (0.013) | (0.011) | (0.010) | (0.009) | (0.012) |
| Enrollment | -0.051** | -0.039** | -0.020 | -0.018 | -0.009 | -0.018 |
| | (0.020) | (0.016) | (0.013) | (0.012) | (0.011) | (0.014) |
| *Baseline mean* | 0.057 | 0.037 | 0.028 | 0.028 | 0.017 | 0.024 |
| *N. of observations* | 7,830 | 7,830 | 7,830 | 7,830 | 7,830 | 7,830 |
| **Panel C. High income** | | | | | | |
| Admission | -0.009 | -0.001 | 0.000 | -0.011* | -0.007* | -0.004 |
| | (0.008) | (0.003) | (0.003) | (0.006) | (0.004) | (0.007) |
| Enrollment | -0.011 | -0.001 | -0.001 | -0.013* | -0.008* | -0.005 |
| | (0.010) | (0.004) | (0.003) | (0.007) | (0.005) | (0.008) |
| *Baseline mean* | 0.011 | 0.000 | 0.001 | 0.010 | 0.006 | 0.007 |
| *N. of observations* | 6,833 | 6,833 | 6,833 | 6,833 | 6,833 | 6,833 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table 3:** Effects of Admission and Enrollment on Criminal Prosecution by Type of Program

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | Share of low-income students | | | Share of students from private high schools | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Low income** | | | | | | |
| | 1st & 2nd quartiles | 3rd quartile | 4th quartile | 1st quartile | 2nd quartile | 3rd & 4th quartiles |
| Admission | -0.100*** | -0.015 | -0.023 | -0.031 | -0.034 | -0.137*** |
| | (0.034) | (0.041) | (0.032) | (0.028) | (0.037) | (0.048) |
| Enrollment | -0.131*** | -0.032 | -0.026 | -0.036 | -0.047 | -0.182*** |
| | (0.045) | (0.077) | (0.035) | (0.032) | (0.051) | (0.065) |
| *Baseline mean* | 0.089 | 0.027 | 0.059 | 0.061 | 0.042 | 0.112 |
| *N. of observations* | 2,559 | 729 | 2,346 | 2,581 | 1,479 | 1,574 |
| **Panel B. High income** | | | | | | |
| | 1st quartile | 2nd quartile | 3rd & 4th quartiles | 1st & 2nd quartiles | 3rd quartile | 4th quartile |
| Admission | -0.006 | 0.002 | -0.023 | -0.022 | 0.002 | -0.002 |
| | (0.013) | (0.013) | (0.019) | (0.022) | (0.015) | (0.012) |
| Enrollment | -0.007 | 0.002 | -0.028 | -0.026 | 0.003 | -0.002 |
| | (0.015) | (0.015) | (0.023) | (0.026) | (0.017) | (0.014) |
| *Baseline mean* | 0.000 | 0.004 | 0.017 | 0.018 | 0.003 | -0.001 |
| *N. of observations* | 1,046 | 1,122 | 1,560 | 1,299 | 861 | 1,568 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and were not formally employed ten years later. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. In each column, samples are split based on the characteristics of the program students apply. In columns (1)-(3), the split is at the quartiles of the share of low-income students admitted to the program. In columns (4)-(6), the split is at the quartiles of the share of admitted students who graduated from a private high school. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table 4:** Effects of Admission and Enrollment on Earnings by Type of Program

| | Dependent variable: log earnings 10 years after application | | | | | | |
|---|---|---|---|---|---|---|---|
| | All | Share of low-income students | | | Share of students from private high schools | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Low income** | | | | | | | |
| | | 1st & 2nd quartiles | 3rd quartile | 4th quartile | 1st quartile | 2nd quartile | 3rd & 4th quartiles |
| Admission | 0.250** | 0.162 | 0.542* | 0.634*** | 0.599*** | 0.304 | 0.013 |
| | (0.109) | (0.195) | (0.307) | (0.146) | (0.137) | (0.306) | (0.197) |
| Enrollment | 0.307** | 0.211 | 1.056 | 0.701*** | 0.673*** | 0.405 | 0.016 |
| | (0.133) | (0.251) | (0.774) | (0.166) | (0.159) | (0.393) | (0.259) |
| *Baseline mean* | 10.409 | 10.431 | 10.415 | 9.770 | 9.855 | 10.119 | 10.687 |
| *N. of observations* | 5,634 | 2,559 | 729 | 2,346 | 2,581 | 1,479 | 1,574 |
| **Panel B. High income** | | | | | | | |
| | | 1st quartile | 2nd quartile | 3rd & 4th quartiles | 1st & 2nd quartiles | 3rd quartile | 4th quartile |
| Admission | 0.027 | 0.297 | -0.146 | 0.038 | 0.084 | -0.143 | 0.057 |
| | (0.112) | (0.227) | (0.187) | (0.201) | (0.195) | (0.298) | (0.197) |
| Enrollment | 0.032 | 0.335 | -0.163 | 0.046 | 0.099 | -0.163 | 0.067 |
| | (0.131) | (0.268) | (0.208) | (0.241) | (0.231) | (0.341) | (0.233) |
| *Baseline mean* | 10.575 | 10.953 | 11.042 | 10.519 | 10.605 | 10.772 | 11.023 |
| *N. of observations* | 3,728 | 1,046 | 1,122 | 1,560 | 1,299 | 861 | 1,568 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on log earnings. Earnings are measured as the sum of all salaries received for 12 months, ten years after the application. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and were not formally employed ten years later. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. In each column, samples are split based on the characteristics of the program students apply. In columns (2)-(4), the split is at the quartiles of the share of low-income students admitted to the program. In columns (5)-(7), the split is at the quartiles of the share of admitted students who graduated from a private high school. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table 5:** Effect of Admission on Educational Attainment and Criminal Prosecution

| | Dependent variable (within 10 years after application) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Graduated from flagship | Attended college | Has college degree | Criminally Prosecuted | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. All sample** | | | | | | | |
| Admission | 0.350*** | 0.052*** | 0.028 | -0.025*** | -0.029*** | -0.030*** | -0.028** |
| | (0.028) | (0.020) | (0.027) | (0.008) | (0.009) | (0.009) | (0.011) |
| *Baseline mean* | 0.283 | 0.847 | 0.740 | 0.036 | 0.036 | 0.036 | 0.036 |
| *N. of observations* | 20,620 | 17,001 | 17,001 | 20,620 | 17,001 | 17,001 | 13,231 |
| **Panel B. Low income** | | | | | | | |
| Admission | 0.364*** | 0.111*** | 0.089* | -0.045*** | -0.047*** | -0.048*** | -0.045** |
| | (0.047) | (0.038) | (0.048) | (0.017) | (0.018) | (0.018) | (0.022) |
| *Baseline mean* | 0.243 | 0.784 | 0.644 | 0.057 | 0.057 | 0.057 | 0.057 |
| *N. of observations* | 7,830 | 7,067 | 7,067 | 7,830 | 7,067 | 7,067 | 5,634 |
| **Panel C. High income** | | | | | | | |
| Admission | 0.324*** | -0.004 | 0.026 | -0.007 | -0.012 | -0.011 | -0.008 |
| | (0.044) | (0.032) | (0.038) | (0.008) | (0.011) | (0.011) | (0.009) |
| *Baseline mean* | 0.321 | 0.903 | 0.822 | 0.011 | 0.011 | 0.011 | 0.011 |
| *N. of observations* | 6,833 | 5,002 | 5,002 | 6,833 | 5,002 | 5,002 | 3,728 |
| **Control variables** | | | | | | | |
| Grad. from flagship | | | | Yes | | | Yes |
| Attended college | | | | | Yes | | Yes |
| Has college degree | | | | | | Yes | Yes |

This table presents the SRD estimates for the effect of admission on the probabilities of graduating from the flagship university (UFPE), in column (1), attending college, in column (2), having a college degree, in column (3), and being criminally prosecuted, in columns (4)-(7), within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and were not formally employed ten years later. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Regressions in columns (4)-(7) include a series of covariates for educational attainment. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table 6:** Effects of Admission and Enrollment on College Attendance by Type of Program

| | Dependent variable: attended college within 10 years after application | | | | | |
|---|---|---|---|---|---|---|
| | Share of low-income students | | | Share of students from private high schools | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Low income** | | | | | | |
| | 1st & 2nd quartiles | 3rd quartile | 4th quartile | 1st quartile | 2nd quartile | 3rd & 4th quartiles |
| Admission | 0.089 | 0.012 | 0.158*** | 0.136*** | 0.027 | 0.065 |
| | (0.067) | (0.115) | (0.050) | (0.051) | (0.095) | (0.080) |
| Enrollment | 0.118 | 0.023 | 0.178*** | 0.157*** | 0.038 | 0.088 |
| | (0.088) | (0.203) | (0.055) | (0.058) | (0.126) | (0.107) |
| *Baseline mean* | 0.819 | 0.950 | 0.767 | 0.783 | 0.839 | 0.867 |
| *N. of observations* | 2,559 | 729 | 2,346 | 2,581 | 1,479 | 1,574 |
| **Panel B. High income** | | | | | | |
| | 1st quartile | 2nd quartile | 3rd & 4th quartiles | 1st & 2nd quartiles | 3rd quartile | 4th quartile |
| Admission | -0.061 | 0.031 | 0.036 | 0.054 | -0.070 | 0.014 |
| | (0.044) | (0.052) | (0.063) | (0.067) | (0.088) | (0.028) |
| Enrollment | -0.071 | 0.035 | 0.044 | 0.064 | -0.080 | 0.016 |
| | (0.052) | (0.058) | (0.076) | (0.079) | (0.100) | (0.033) |
| *Baseline mean* | 0.988 | 0.917 | 0.875 | 0.861 | 0.911 | 0.967 |
| *N. of observations* | 1,046 | 1,122 | 1,560 | 1,299 | 861 | 1,568 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on the probability of attending any college within 10 years following the application. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and were not formally employed ten years later. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. In each column, samples are split based on the characteristics of the program students apply. In columns (1)-(3), the split is at the quartiles of the share of low-income students admitted to the program. In columns (4)-(6), the split is at the quartiles of the share of admitted students who graduated from a private high school. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table 7:** Effect of Admission on the Quality of Attended HE Institution

| | Dependent variable: graduated from a high-quality college | | | | | |
|---|---|---|---|---|---|---|
| | All sample | | | With college degree | | |
| | | Share of low-income students | | | Share of low-income students | |
| | All | High | Low | All | High | Low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | 0.389*** | 0.329*** | 0.406*** | 0.351*** | 0.239*** | 0.371*** |
| | (0.043) | (0.073) | (0.068) | (0.049) | (0.084) | (0.082) |
| Enrollment | 0.461*** | 0.375*** | 0.505*** | 0.427*** | 0.277*** | 0.484*** |
| | (0.049) | (0.080) | (0.078) | (0.055) | (0.094) | (0.094) |
| *Baseline mean* | 0.440 | 0.478 | 0.403 | 0.458 | 0.543 | 0.402 |
| *N. of observations* | 5,006 | 2,359 | 2,647 | 3,345 | 1,593 | 1,752 |
| **Panel B. Low income** | | | | | | |
| Admission | 0.442*** | 0.221* | 0.711*** | 0.393*** | 0.127 | 0.536*** |
| | (0.085) | (0.121) | (0.132) | (0.097) | (0.142) | (0.180) |
| Enrollment | 0.510*** | 0.257* | 0.867*** | 0.455*** | 0.144 | 0.798*** |
| | (0.094) | (0.138) | (0.143) | (0.106) | (0.159) | (0.214) |
| *Baseline mean* | 0.378 | 0.518 | 0.131 | 0.426 | 0.609 | 0.143 |
| *N. of observations* | 1,707 | 858 | 849 | 1,144 | 596 | 548 |
| **Panel C. High income** | | | | | | |
| Admission | 0.312*** | 0.312** | 0.330*** | 0.278*** | 0.265* | 0.288*** |
| | (0.070) | (0.138) | (0.079) | (0.079) | (0.145) | (0.091) |
| Enrollment | 0.376*** | 0.373** | 0.400*** | 0.351*** | 0.342* | 0.360*** |
| | (0.081) | (0.158) | (0.092) | (0.093) | (0.179) | (0.105) |
| *Baseline mean* | 0.504 | 0.495 | 0.495 | 0.517 | 0.522 | 0.505 |
| *N. of observations* | 1,784 | 672 | 1,112 | 1,158 | 422 | 736 |

This table presents the SRD estimates for the effect of admission on the probability of graduating from a high-quality HE institution. Quality is assessed by the Ministry of Education, which gives each HE institution a score from 0 to 5. The dependent variable is equal to one if the applicant graduated from a institution whose score was equal to or greater than 4, and zero otherwise. The sample includes only applicants whose years of schooling is observed on RAIS; it also excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. In columns (1)-(3), we include all applicants who did not have a college degree or whose college quality is observed. In columns (4)-(6), we include only applicants who have a college degree and whose quality is observed. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. In columns (2)-(3) and (5)-(6), samples are split at the median share of low-income students admitted to the program. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table 8:** Effect Admission on Civil Prosecutions

| | Dependent variable: prosecuted in (within 10 years after application) | | |
|---|---|---|---|
| | Divorce trial | Collection lawsuit | Other civil procedure |
| | (1) | (2) | (3) |
| **Panel A. All sample** | | | |
| Admission | 0.000 | 0.009 | 0.014 |
| | (0.003) | (0.015) | (0.019) |
| *Baseline mean* | 0.005 | 0.062 | 0.102 |
| *N. of observations* | 20,620 | 20,620 | 20,620 |
| **Panel B. Low income** | | | |
| Admission | -0.004 | 0.004 | 0.043 |
| | (0.010) | (0.026) | (0.032) |
| *Baseline mean* | 0.012 | 0.108 | 0.140 |
| *N. of observations* | 7,830 | 7,830 | 7,830 |
| **Panel C. High income** | | | |
| Admission | 0.001 | 0.019 | 0.022 |
| | (0.004) | (0.016) | (0.022) |
| *Baseline mean* | 0.003 | 0.018 | 0.060 |
| *N. of observations* | 6,833 | 6,833 | 6,833 |

This table presents the SRD estimates for the effect of admission on the probabilities of being in a divorce trial, in column (1), sued for non-payment, in column (2), and prosecuted in another type of civil case, in column (3), within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

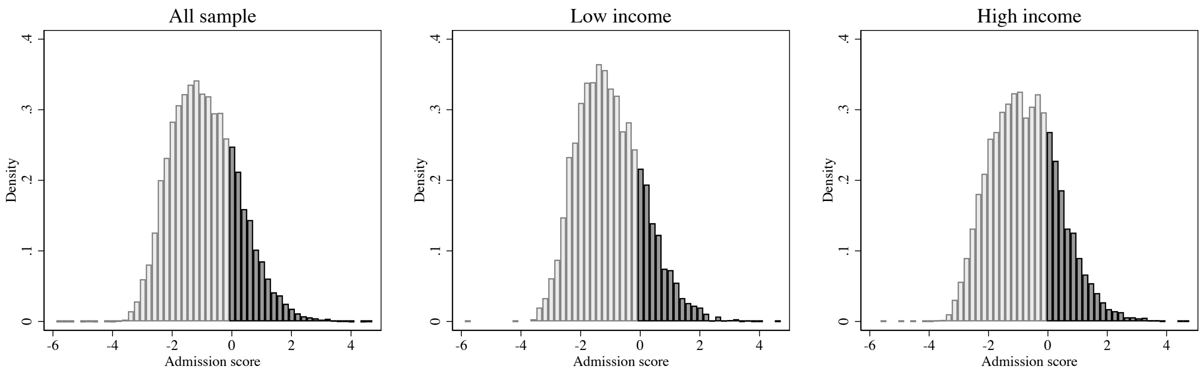
# A Additional Data Sources

To obtain the academic degrees held by individuals in our sample, we use a web search platform called *Escavador*. Its search engine finds up-to-date information of Brazilian citizens by scraping official gazettes and online curricula vitae. Then, using individuals' full names, we attempt to identify their attended institution and program of study, as well as graduation year in case they hold an academic degree. With this engine, we obtain the academic information for 33% of the college graduates in our sample.

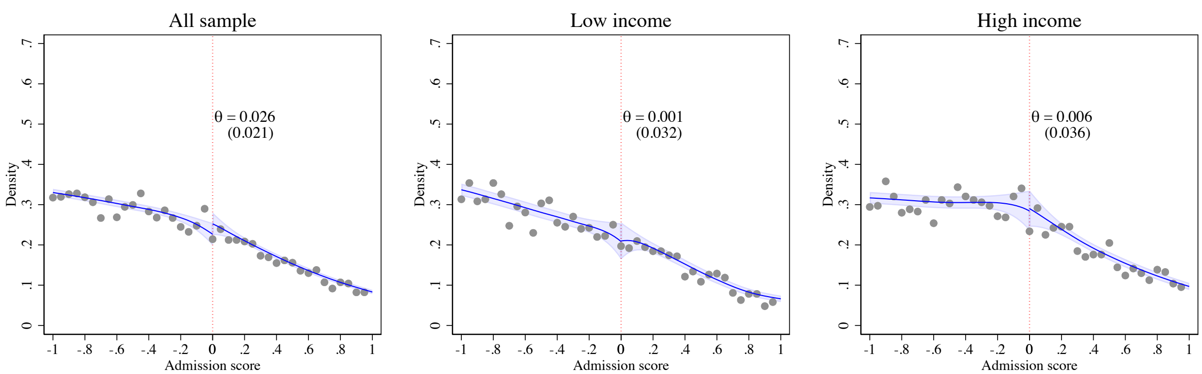
The academic information is then matched with data from the Ministry of Education (MEC), which assesses the quality of all graduate and undergraduate programs in Brazil. The quality score per program takes into account its graduates' performance in a national standardized exam (*Exame Nacional de Desempenho dos Estudantes*, ENADE), infrastructure (e.g., number of faculty members, their academic degree, and quality of libraries and laboratories), and research output (in the case of graduate programs). The institutional score (*Índice Geral dos Cursos*, IGC) is a weighted average of quality scores of all programs in the same institution. This score varies from zero to five. To be recognized as a high-quality institution, the IGC must be equal to or greater than four. Every year, about 20% of HE institutions in Brazil are classified as high-quality.

**Figure A1:** Distribution of Admission Scores and Density Continuity Test

**(a)** Distribution



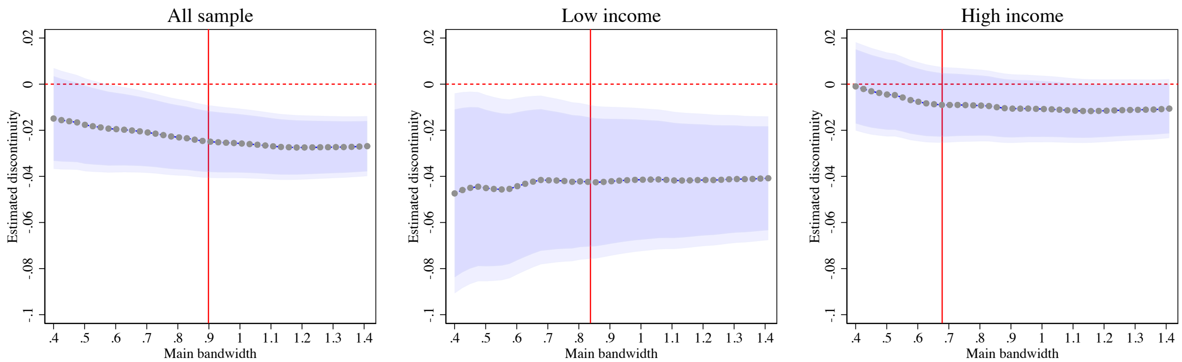

**(b)** Density Continuity Test



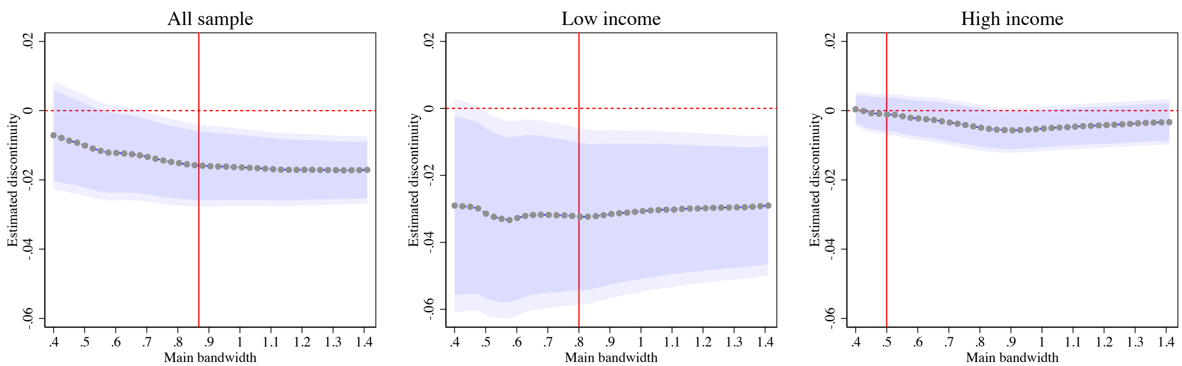

The admission score (x-axis) is standardized using the admission cutoff and the standard deviation of all applicants that passed to the second round by program and year. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Panel (a) presents the histograms of the admission scores. Panel (b) presents the estimated density (y-axis) near the admission cutoff. Grey dots represent mean values within bins of 0.05 standard deviations in the admission score. Shaded areas represent robust confidence interval at 95% level. $\theta$ is the Cattaneo, Jansson and Ma's (2020) estimator for log density discontinuity, with robust standard error in parenthesis. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Figure A2:** Estimated Effect of Admission on Criminal Prosecution Using Different Bandwidths

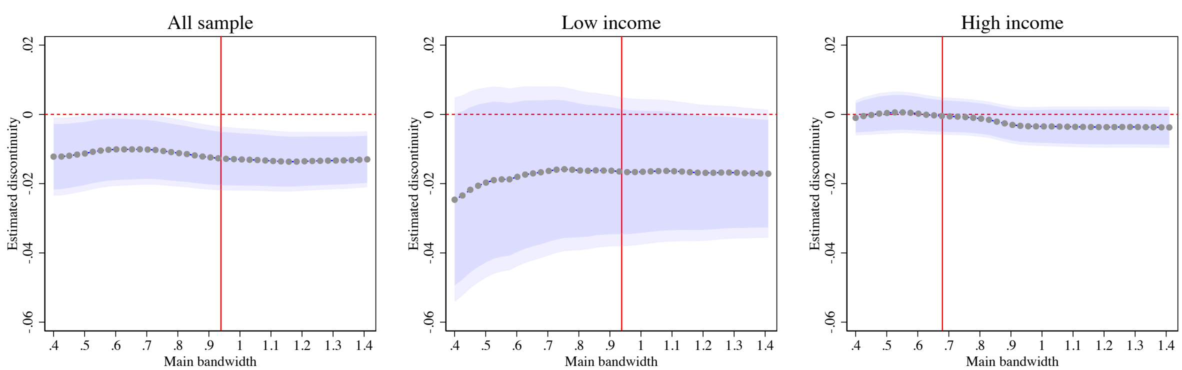
**(a)** All crimes




**(b)** Violent crimes



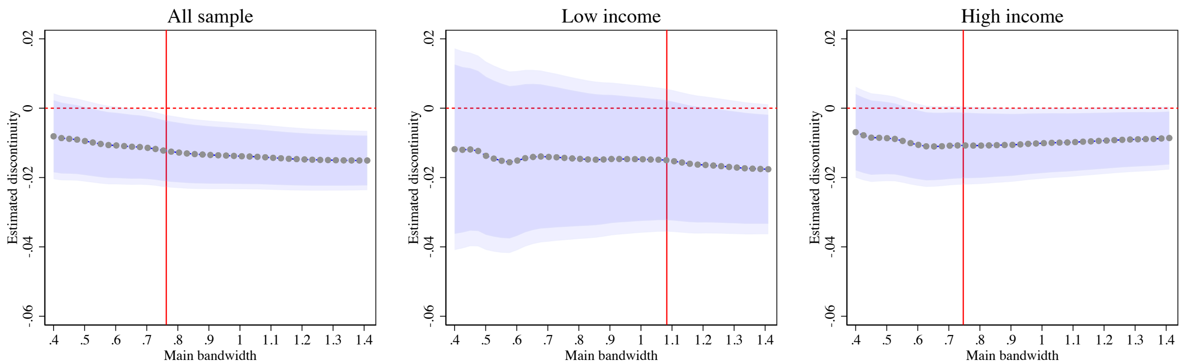

**(c)** Property crimes



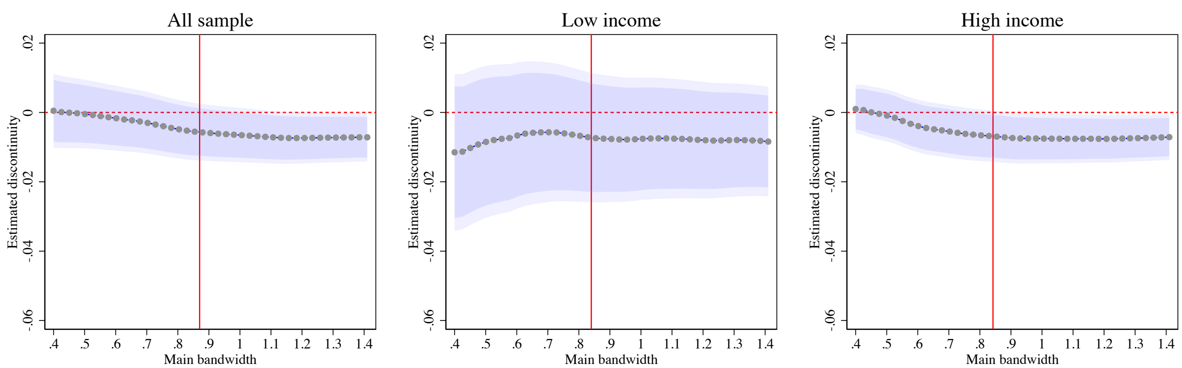

(continuing)

**Figure A2** – continued from the previous page

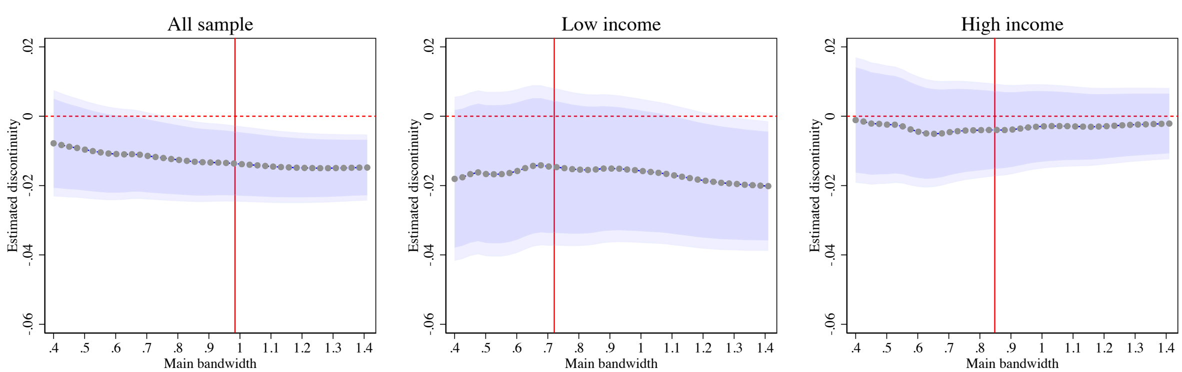
### **(d)** Against the public interest




### **(e)** Traffic-related crimes



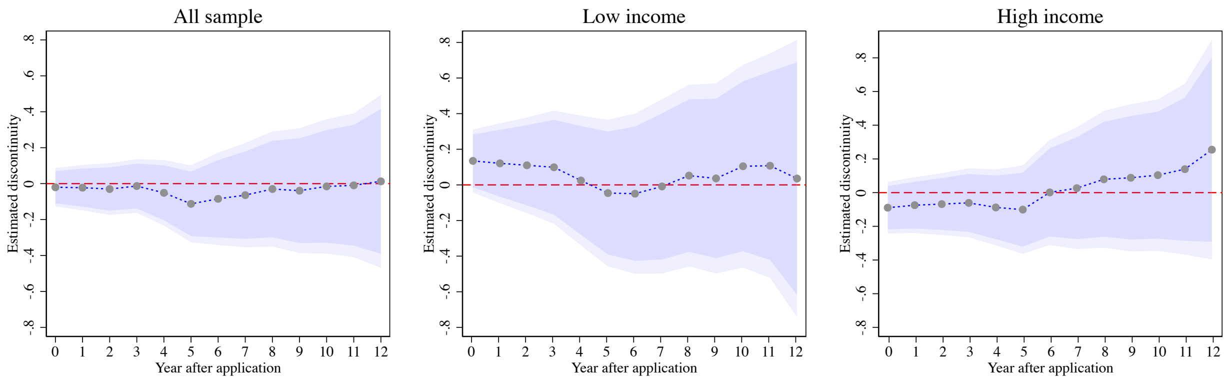

### **(f)** Unclassified crimes



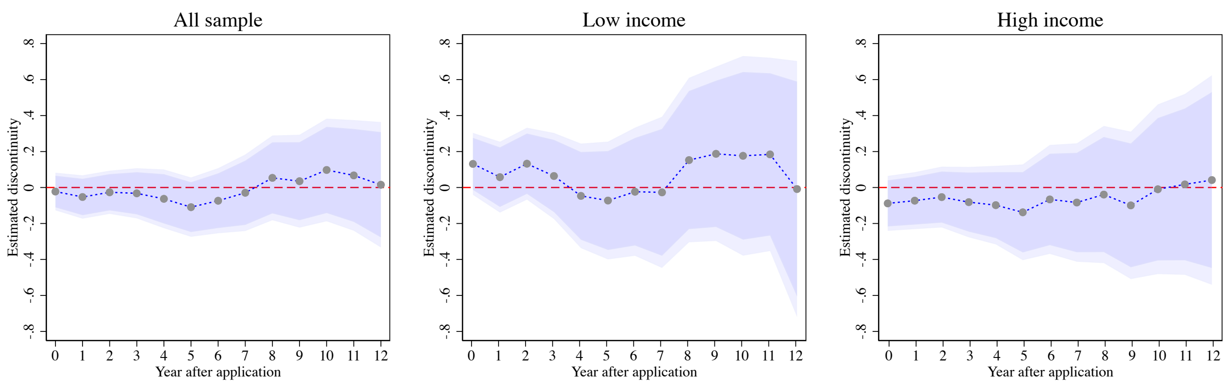

This figure presents the SRD estimates for the admission effect (y-axis), as in Table 2, but using different bandwidths (x-axis). SRDs are estimated using a triangular kernel. The vertical line indicates the main bandwidth obtained with the procedure proposed by Calonico, Cattaneo and Titiunik (2014). Shaded areas represent the robust confidence intervals at the 90% (darker) and 95% (lighter) levels.

**Figure A3:** Effect of Admission on Work Experience and Job Tenure by Year After Applying to the Flagship University

**(a)** Work Experience

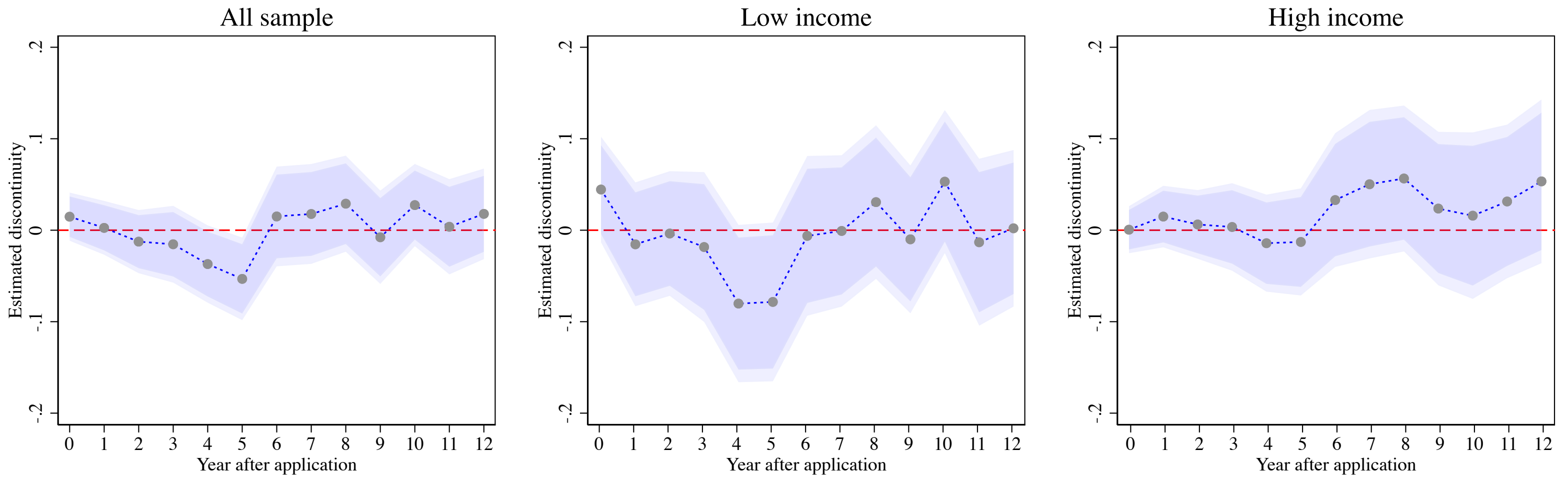



**(b)** Job Tenure



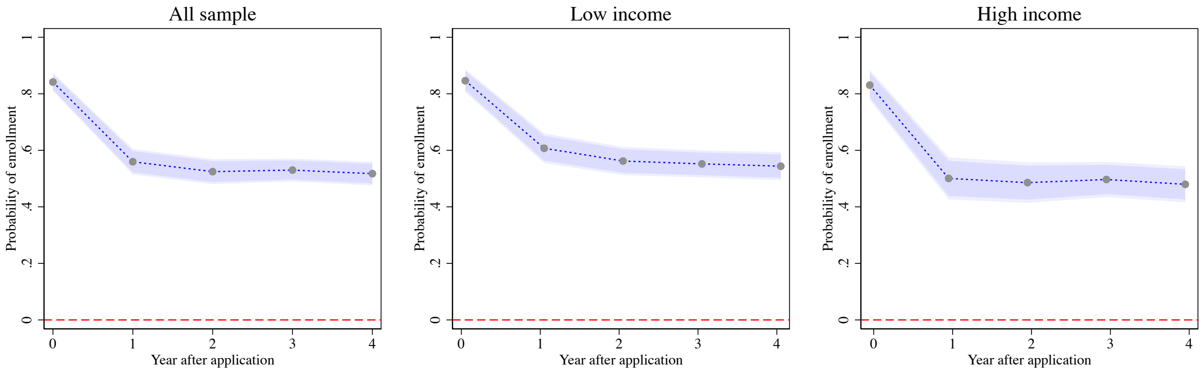

This figure presents the SRD estimates for work experience and job tenure (y-axis) in each year after applying to the university (x-axis). In panel (a), the dependent variable is the cumulative number of months formally employed up to a certain year after the application. In panel (b), the dependent variable is the cumulative number of months working for the current employer. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence intervals at 90% (darker) and 95% (lighter) levels. Standard errors are clustered at the applicant level.

**Figure A4:** Effect of Admission on the Share of Days Worked per Year After Applying to the Flagship University



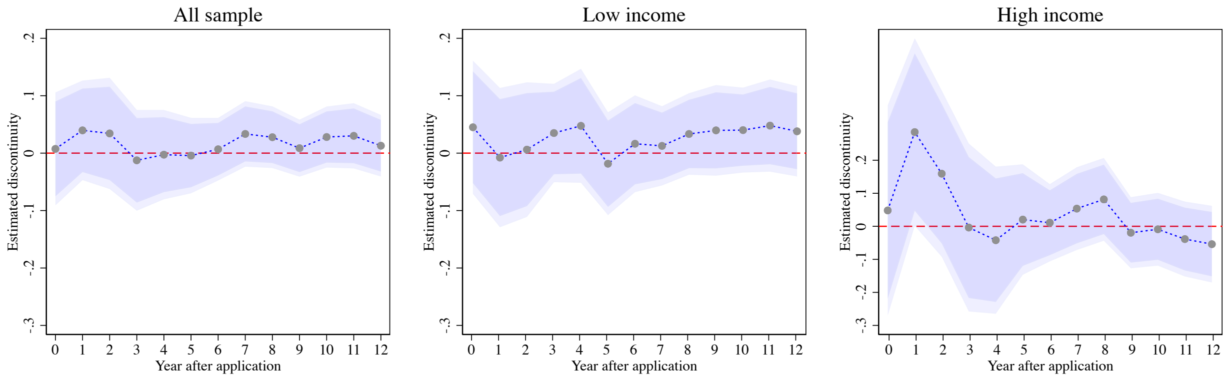

This figure presents the SRD estimates for the proportion of days formally employed (y-axis) in each year after applying to the university (x-axis). The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence intervals at 90% (darker) and 95% (lighter) levels. Standard errors are clustered at the applicant level.

**Figure A5:** Effect of Admission on the Probability of Enrollment at Flagship University Over the Years




This figure presents SRD estimates for the effects of admission on enrollment in the flagship university for each year after application. The dependent variable equals 1 if the applicant is enrolled in the university in the given year and 0 otherwise. The first graph on the left includes all applicants in our sample, excluding those who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. In the other two graphs, sample is split based on the income reported on the application. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each point in these graphs represents a SRD estimate, estimated using triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence interval at 90% (darker) and 95% (lighter) levels.

**Figure A6:** Effect of Admission on Migration by Year After Applying to the Flagship University




This figure presents the SRD estimates for migration (y-axis) in each year after applying to the university (x-axis). For each year, the dependent variable is equal to one if the applicant does not work in the same state as the one declared during the application and zero otherwise. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Shaded areas represent robust confidence intervals at 90% (darker) and 95% (lighter) levels. Standard errors are clustered at the applicant level.

**Table A1:** Higher Education Institutions in the State of Pernambuco, Brazil

| Institution | Rank | Type | N. of programs | Undergrad. students | Graduate students | Share of faculty with Ph.D. | Institution | Rank | Type | N. of programs | Undergrad. students | Graduate students | Share of faculty with Ph.D. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **UFPE** | 46 | **Free university** | **105** | **32,137** | **3,971** | **0.709** | FJN | 1,286 | Paid college | 13 | 5,626 | 786 | 0.151 |
| UFRPE | 100 | Free university | 47 | 11,572 | 1,182 | 0.747 | FPDMB | 1,306 | Paid college | 9 | 1,143 | 239 | 0.075 |
| UNIVASF* | 204 | Free university | 11 | 3,296 | 360 | 0.544 | FCHPE | 1,349 | Paid college | 3 | 897 | 187 | 0.217 |
| FNR | 241 | Paid college | 5 | 1,153 | 59 | 0.099 | FACHO | 1,367 | Paid college | 6 | 1,412 | 245 | 0.162 |
| FSH | 285 | Paid college | 3 | 1,509 | 205 | 0.250 | FALUB | 1,373 | Paid college | 4 | 1,029 | 253 | 0.113 |
| FACETEG* | 292 | Paid college | 2 | 675 | 90 | 0.100 | FAREC | 1,375 | Paid college | 8 | 1,290 | 305 | 0.047 |
| FOCCA | 356 | Paid college | 8 | 1,888 | 190 | 0.211 | IBRATEC | 1,399 | Paid college | 6 | 963 | 153 | 0.058 |
| FACIPE | 449 | Paid college | 16 | 3,051 | 602 | 0.329 | FADIC | 1,536 | Paid college | 4 | 1,011 | 116 | 0.408 |
| FAINTVISA* | 453 | Paid college | 18 | 2,580 | 489 | 0.185 | FACESF | 1,537 | Paid college | 2 | 979 | 82 | 0.081 |
| FASNE | 465 | Paid college | 4 | 759 | 71 | 0.174 | FAFICA* | 1,545 | Paid college | 11 | 1,123 | 350 | 0.086 |
| IBGM / FGM | 479 | Paid college | 22 | 6,022 | 1,157 | 0.232 | FACAPE* | 1,558 | Paid college | 10 | 3,829 | 430 | 0.087 |
| FACET* | 495 | Paid college | 2 | 311 | 75 | 0.074 | IESO | 1,580 | Paid college | 2 | 287 | 91 | 0.136 |
| FBV | 503 | Paid college | 43 | 4,957 | 650 | 0.234 | FAMA | 1,601 | Paid college | 3 | 386 | 154 | 0.094 |
| FEPAM | 529 | Paid college | 1 | 104 | 15 | 0.087 | FIS | 1,624 | Paid college | 9 | 2,122 | 281 | 0.076 |
| FACIG | 560 | Paid college | 8 | 1,263 | 235 | 0.204 | FACOTTUR | 1,625 | Paid college | 11 | 1,192 | 109 | 0.180 |
| FIR | 630 | Paid college | 24 | 10,632 | 1,061 | 0.185 | FAGA* | 1,715 | Paid college | 3 | 505 | 100 | 0.093 |
| UNIFAVIP* | 633 | Paid college | 30 | 8,825 | 1,016 | 0.180 | IPESU | 1,721 | Paid college | 11 | 1,653 | 260 | 0.056 |
| FG | 649 | Paid college | 40 | 11,003 | 1,686 | 0.117 | ISEF* | 1,733 | Paid college | 1 | 89 | 44 | 0 |
| FAJOLCA | 654 | Paid college | 3 | 596 | 123 | 0.176 | FATIN | 1,768 | Paid college | 2 | 634 | 160 | 0.111 |
| FCHE | 692 | Paid college | 5 | 1,815 | 338 | 0.299 | UNESJ | 1,790 | Paid college | 20 | 2,695 | 543 | 0.114 |
| FMN Caruaru | 703 | Paid college | 12 | 2,737 | 241 | 0.107 | ESSA* | 1,815 | Paid college | 4 | 553 | 92 | 0.129 |
| FACHUSST | 707 | Paid college | 1 | 173 | 42 | 0.278 | CESA* | 1,816 | Paid college | 7 | 1,149 | 306 | 0.099 |
| UPE | 712 | Free university | 56 | 14,313 | 1,631 | 0.463 | ESM | 1,819 | Paid college | 2 | 296 | 43 | 0.103 |
| UNICAP | 737 | Paid university | 37 | 9,805 | 1,464 | 0.440 | FASUP | 1,826 | Paid college | 2 | 160 | 4 | 0.308 |
| FAC. S. MIGUEL | 779 | Paid college | 18 | 3,247 | 170 | 0.233 | FACEG | 1,856 | Paid college | 1 | 608 | 56 | 0.077 |
| IFPE | 792 | Free college | 17 | 2,798 | 262 | 0.239 | FSM | 1,917 | Paid college | 2 | 12 | 0 | 0.167 |
| IESP | 796 | Paid college | 1 | 45 | 33 | 0 | CESVASF* | 1,918 | Paid college | 8 | 892 | 94 | 0.022 |
| FACOL* | 803 | Paid college | 13 | 2,974 | 467 | 0.185 | FAMASUL* | 1,926 | Paid college | 6 | 929 | 309 | 0.075 |
| FIBAM | 829 | Paid college | 14 | 1,579 | 231 | 0.200 | FDG* | 1,928 | Paid college | 1 | 1,054 | 144 | 0.081 |
| FACCOR | 831 | Paid college | 1 | 74 | 18 | 0.111 | ISES* | 1,958 | Paid college | 1 | 64 | 24 | 0.091 |
| FPS | 839 | Paid college | 6 | 1,837 | 244 | 0.221 | FACIAGRA* | 1,967 | Paid college | 2 | 255 | 59 | 0.043 |
| ASCES* | 880 | Paid college | 17 | 4,425 | 673 | 0.288 | FBJ | 1,969 | Paid college | 10 | 1,828 | 350 | 0.049 |
| UNINASSAU | 886 | Paid college | 42 | 21,292 | 2,170 | 0.197 | ISEP* | 1,970 | Paid college | 2 | 920 | 222 | 0.143 |
| FAC. STA. EM. | 981 | Paid college | 7 | 854 | 144 | 0.135 | UNESF | 1,981 | Paid college | 8 | 547 | 97 | 0.078 |
| FAESC* | 995 | Paid college | 6 | 1,006 | 208 | 0.205 | FAFOPST* | 1,986 | Paid college | 5 | 576 | 155 | 0.136 |
| FOR | 1,031 | Paid college | 1 | 127 | 21 | 0.455 | FACISST* | 2,011 | Paid college | 1 | 234 | 54 | 0.148 |
| FADIRE* | 1,088 | Paid college | 3 | 623 | 239 | 0.094 | FATEC | 2,025 | Paid college | 1 | 110 | 13 | 0.037 |
| FAC. JOAQ. NAB. | 1,101 | Paid college | 4 | 378 | 31 | 0.286 | FACIP | 2,027 | Paid college | 1 | 161 | 48 | 0.043 |
| FCR | 1,130 | Paid college | 4 | 617 | 174 | 0.106 | FACHUCA | 2,036 | Paid college | 4 | 768 | 70 | 0.060 |
| FJN | 1,143 | Paid college | 11 | 3,322 | 464 | 0.176 | FACHUSC* | 2,056 | Paid college | 7 | 1,219 | 358 | 0.031 |
| IF Sertão* | 1,176 | Free college | 12 | 1,724 | 140 | 0.225 | FAFOPA | 2,057 | Paid college | 7 | 616 | 168 | 0.054 |
| FASC | 1,180 | Paid college | 3 | 425 | 73 | 0.102 | FACISA* | 2,083 | Paid college | 2 | 567 | 119 | 0.032 |
| FAFOPAI* | 1,241 | Paid college | 4 | 551 | 149 | 0.036 | FACAL* | 2,092 | Paid college | 6 | 820 | 98 | 0.054 |
| SENACPE | 1,274 | Paid college | 5 | 791 | 191 | 0.130 | FACRUZ* | 2,102 | Paid college | 1 | 44 | 11 | 0.095 |
| FAFIRE | 1,284 | Paid college | 13 | 2,278 | 447 | 0.164 | UNIVERSO | - | Paid college | 13 | 3,988 | 609 | 0.164 |

This table shows the profile of higher education institutions in Pernambuco and their national rank position out of 2,132 institutions evaluated in 2016. * are Paid colleges located outside the metropolitan area of Recife. In 2006, there were 78 higher education institutions in Pernambuco.

**Table A2:** Characteristics of UFPE Applicants and Admitted Students
Compared to High School Graduates and First-Year College Students

| | Brazil | | Northeast Region | | State of Pernambuco | | UFPE candidates | |
|---|---|---|---|---|---|---|---|---|
| | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. |
| | **Last year of high school** | | | | | | **Applicants** | |
| Female | 0.557 | 0.497 | 0.583 | 0.493 | 0.569 | 0.495 | 0.556 | 0.497 |
| Age | 21.32 | 7.788 | 21.54 | 7.389 | 22.13 | 8.044 | 21.67 | 5.715 |
| Age $\leq$ 21 | 0.751 | 0.433 | 0.724 | 0.447 | 0.692 | 0.462 | 0.701 | 0.458 |
| White | 0.496 | 0.500 | 0.313 | 0.464 | 0.378 | 0.485 | 0.498 | 0.500 |
| From public high school | 0.809 | 0.393 | 0.838 | 0.369 | 0.826 | 0.379 | 0.373 | 0.483 |
| Employed | 0.440 | 0.496 | 0.409 | 0.492 | 0.379 | 0.485 | 0.243 | 0.429 |
| Both parents with college degree | 0.128 | 0.334 | 0.064 | 0.245 | 0.079 | 0.270 | 0.162 | 0.368 |
| Neither parent with college degree | 0.645 | 0.479 | 0.761 | 0.426 | 0.733 | 0.442 | 0.641 | 0.480 |
| Number of observations | 34,405 | | 10,629 | | 2,246 | | 513,465 | |
| | **First year of college** | | | | | | **Admitted** | |
| Female | 0.576 | 0.494 | 0.616 | 0.486 | 0.616 | 0.487 | 0.515 | 0.500 |
| Age | 25.16 | 8.355 | 25.86 | 8.434 | 25.58 | 8.265 | 21.75 | 5.639 |
| Age $\leq$ 21 | 0.468 | 0.499 | 0.415 | 0.493 | 0.444 | 0.497 | 0.697 | 0.460 |
| White | 0.624 | 0.484 | 0.413 | 0.492 | 0.480 | 0.500 | 0.540 | 0.498 |
| From public high school* | - | - | - | - | - | - | 0.309 | 0.462 |
| Employed | 0.651 | 0.477 | 0.610 | 0.488 | 0.595 | 0.491 | 0.207 | 0.405 |
| Both parents with college degree | 0.198 | 0.399 | 0.122 | 0.327 | 0.120 | 0.325 | 0.226 | 0.418 |
| Neither parent with college degree | 0.518 | 0.500 | 0.600 | 0.490 | 0.558 | 0.497 | 0.544 | 0.498 |
| Number of observations | 17,022 | | 4,327 | | 771 | | 63,878 | |

Data for Brazil, the Northeast and Pernambuco come from the National Household Survey (*Pesquisa Nacional por Amostra de Domicílios*, PNAD) from 2002 to 2012. The sample of students in the 'last year of high school' also includes those taking pre-college preparatory course. Data for UFPE candidates come from the admission committee (*Comissão para o Vestibular*, COVEST). *In PNAD, we cannot observe previous studies for students currently enrolled in any educational institution.

**Table A3:** Difference in Applicants' Characteristics Across the Admission Cutoff

| | | | | Found on RAIS | | |
|---|---|---|---|---|---|---|
| | All sample | Low income | High income | All sample | Low income | High income |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | 0.001 | -0.046 | 0.048 | -0.004 | -0.072 | 0.082 |
| | (0.028) | (0.047) | (0.045) | (0.032) | (0.058) | (0.055) |
| Age | -0.097 | -0.139 | -0.104 | -0.043 | -0.017 | 0.025 |
| | (0.137) | (0.289) | (0.191) | (0.153) | (0.306) | (0.235) |
| Number of previous attempts | 0.017 | 0.010 | 0.049 | 0.013 | -0.016 | 0.091 |
| | (0.064) | (0.095) | (0.108) | (0.073) | (0.113) | (0.127) |
| Attended preparatory course | -0.034 | -0.040 | 0.000 | -0.018 | -0.031 | 0.009 |
| | (0.028) | (0.053) | (0.045) | (0.031) | (0.061) | (0.053) |
| Attended private high school | -0.026 | -0.040 | -0.028 | -0.013 | -0.027 | -0.020 |
| | (0.024) | (0.048) | (0.025) | (0.030) | (0.051) | (0.030) |
| *Income brackets* | | | | | | |
| Low income (< 1,000 BRL/month) | 0.017 | | | 0.014 | | |
| | (0.026) | | | (0.028) | | |
| High income (> 2,000 BRL/month) | -0.030 | | | -0.009 | | |
| | (0.025) | | | (0.030) | | |
| One parent has college degree | -0.020 | -0.051 | -0.027 | -0.003 | -0.042 | -0.018 |
| | (0.029) | (0.037) | (0.037) | (0.032) | (0.036) | (0.044) |
| One parent is underemployed | -0.005 | 0.046 | -0.033 | -0.010 | 0.052 | -0.036 |
| | (0.020) | (0.050) | (0.025) | (0.027) | (0.049) | (0.034) |
| One parent is an entrepreneur | -0.015 | -0.043 | 0.001 | 0.006 | -0.057 | 0.020 |
| | (0.022) | (0.031) | (0.044) | (0.027) | (0.035) | (0.047) |
| Lives in MAR | -0.012 | -0.012 | -0.036 | -0.022 | -0.038 | -0.032 |
| | (0.014) | (0.030) | (0.026) | (0.016) | (0.029) | (0.030) |
| *Main reason to choose program of study* | | | | | | |
| Career prestige | 0.004 | -0.003 | -0.001 | 0.007 | 0.005 | 0.001 |
| | (0.008) | (0.015) | (0.013) | (0.010) | (0.017) | (0.017) |
| Quality of the program | 0.000 | -0.019 | 0.019 | -0.009 | -0.019 | -0.003 |
| | (0.015) | (0.027) | (0.023) | (0.017) | (0.028) | (0.030) |
| Personal self-fulfilment | -0.009 | 0.026 | -0.071 | 0.000 | 0.018 | -0.050 |
| | (0.027) | (0.049) | (0.045) | (0.033) | (0.050) | (0.055) |
| Other reasons | 0.006 | -0.009 | 0.036 | 0.002 | -0.002 | 0.026 |
| | (0.026) | (0.045) | (0.038) | (0.031) | (0.053) | (0.045) |
| *Main reason to apply to UFPE* | | | | | | |
| No tuition fees | 0.038 | 0.035 | 0.014 | 0.045 | 0.055 | -0.017 |
| | (0.027) | (0.050) | (0.034) | (0.032) | (0.056) | (0.044) |
| University's prestige | -0.019 | 0.015 | -0.032 | -0.028 | -0.011 | -0.011 |
| | (0.024) | (0.038) | (0.038) | (0.029) | (0.044) | (0.052) |
| Other reasons | -0.025 | -0.039 | 0.017 | -0.020 | -0.032 | 0.030 |
| | (0.027) | (0.046) | (0.039) | (0.032) | (0.053) | (0.055) |
| Number of observations | 20,368-20,620 | 7,678-7,830 | 6,793-6,833 | 14,800-14,989 | 6,054-6,178 | 4,402-4,428 |

This table presents the SRD estimates for the effect of admission on the pre-determined characteristics of applicants. Each column shows the estimates for a different sample. All these samples exclude applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. In the last three columns, samples exclude applicants who are not found on RAIS (never had a formal occupation). 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Table A4:** Effects of Admission and Enrollment on the Criminal Prosecution by Parental Education

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Neither parent has college degree** | | | | | | |
| Admission | -0.037*** | -0.030*** | -0.019** | -0.010 | -0.012* | -0.023*** |
| | (0.014) | (0.010) | (0.009) | (0.008) | (0.007) | (0.009) |
| Enrollment | -0.042*** | -0.035*** | -0.022** | -0.012 | -0.013* | -0.027*** |
| | (0.015) | (0.012) | (0.010) | (0.009) | (0.008) | (0.010) |
| *Baseline mean* | 0.055 | 0.037 | 0.028 | 0.018 | 0.019 | 0.033 |
| *N. of observations* | 11,309 | 11,309 | 11,309 | 11,309 | 11,309 | 11,309 |
| **Panel B. At least one parent has college degree** | | | | | | |
| Admission | -0.011 | 0.000 | -0.005 | -0.015** | 0.003** | -0.006 |
| | (0.009) | (0.005) | (0.004) | (0.006) | (0.001) | (0.005) |
| Enrollment | -0.013 | 0.000 | -0.007 | -0.018** | 0.004** | -0.008 |
| | (0.010) | (0.007) | (0.005) | (0.007) | (0.002) | (0.007) |
| *Baseline mean* | 0.017 | 0.004 | 0.006 | 0.014 | 0.002 | 0.009 |
| *N. of observations* | 9,342 | 9,342 | 9,342 | 9,342 | 9,342 | 9,342 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. Panel A only considers applicants whose parents did not have a college degree. Panel B only considers applicants with at least one parent having a college degree. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table A5:** Effects of Admission and Enrollment on the Criminal Prosecution of Male Students

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.035** | -0.033*** | -0.033*** | -0.025** | -0.015 | -0.027** |
| | (0.017) | (0.012) | (0.009) | (0.010) | (0.009) | (0.013) |
| Enrollment | -0.042** | -0.039*** | -0.040*** | -0.031** | -0.017 | -0.033** |
| | (0.021) | (0.015) | (0.011) | (0.012) | (0.011) | (0.015) |
| *Baseline mean* | 0.063 | 0.043 | 0.035 | 0.034 | 0.024 | 0.040 |
| *N. of observations* | 8,686 | 8,686 | 8,686 | 8,686 | 8,686 | 8,686 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.070* | -0.075** | -0.057** | -0.019 | -0.025 | -0.040 |
| | (0.040) | (0.032) | (0.027) | (0.030) | (0.024) | (0.028) |
| Enrollment | -0.092* | -0.098** | -0.074** | -0.025 | -0.032 | -0.053 |
| | (0.052) | (0.041) | (0.034) | (0.038) | (0.031) | (0.036) |
| *Baseline mean* | 0.100 | 0.080 | 0.067 | 0.049 | 0.043 | 0.056 |
| *N. of observations* | 3,039 | 3,039 | 3,039 | 3,039 | 3,039 | 3,039 |
| **Panel C. High income** | | | | | | |
| Admission | -0.021 | -0.004 | -0.003 | -0.022* | -0.012 | -0.004 |
| | (0.017) | (0.006) | (0.006) | (0.012) | (0.008) | (0.012) |
| Enrollment | -0.025 | -0.004 | -0.003 | -0.026* | -0.014 | -0.005 |
| | (0.020) | (0.007) | (0.007) | (0.014) | (0.009) | (0.015) |
| *Baseline mean* | 0.025 | 0.001 | 0.004 | 0.019 | 0.010 | 0.011 |
| *N. of observations* | 3,172 | 3,172 | 3,172 | 3,172 | 3,172 | 3,172 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample includes only male applicants and excludes those who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table A6:** Effects of Admission and Enrollment on the Criminal Prosecution of Female Students

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.015* | -0.005 | 0.001 | -0.010* | 0.001 | -0.002 |
| | (0.008) | (0.005) | (0.005) | (0.005) | (0.001) | (0.005) |
| Enrollment | -0.018* | -0.006 | 0.001 | -0.012* | 0.001 | -0.003 |
| | (0.010) | (0.006) | (0.006) | (0.006) | (0.001) | (0.006) |
| *Baseline mean* | 0.015 | 0.005 | 0.002 | 0.008 | 0.000 | 0.005 |
| *N. of observations* | 11,896 | 11,896 | 11,896 | 11,896 | 11,896 | 11,896 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.031* | -0.008 | -0.002 | -0.017 | 0.002 | -0.003 |
| | (0.019) | (0.013) | (0.011) | (0.011) | (0.003) | (0.010) |
| Enrollment | -0.036* | -0.009 | -0.002 | -0.020 | 0.002 | -0.004 |
| | (0.021) | (0.014) | (0.013) | (0.013) | (0.003) | (0.011) |
| *Baseline mean* | 0.028 | 0.010 | 0.004 | 0.009 | 0.001 | 0.004 |
| *N. of observations* | 4,771 | 4,771 | 4,771 | 4,771 | 4,771 | 4,771 |
| **Panel C. High income** | | | | | | |
| Admission | 0.002 | 0.002 | 0.000 | -0.001 | -0.002 | 0.000 |
| | (0.002) | (0.002) | (0.000) | (0.002) | (0.002) | (0.003) |
| Enrollment | 0.002 | 0.002 | 0.000 | -0.001 | -0.003 | -0.001 |
| | (0.003) | (0.003) | (0.000) | (0.003) | (0.003) | (0.003) |
| *Baseline mean* | -0.002 | -0.002 | 0.000 | 0.001 | 0.002 | 0.000 |
| *N. of observations* | 3,656 | 3,656 | 3,656 | 3,656 | 3,656 | 3,656 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample includes only female applicants and excludes those who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table A7:** Effects of Admission and Enrollment on Criminal Prosecution, Estimated Using Quadratic Polynomials and Matched Applicants

| | Dependent variable: criminally prosecuted within 10 years | | | |
|---|---|---|---|---|
| | | Matched applicants per program cohort (N. of obs. above and below the cutoff) | | |
| | Quadratic polynomial | 4 applicants | 5 applicants | 6 applicants |
| | (1) | (2) | (3) | (4) |
| **Panel A. All sample** | | | | |
| Admission | -0.026*** | -0.033** | -0.025* | -0.023** |
| | (0.008) | (0.015) | (0.013) | (0.011) |
| Enrollment | -0.031*** | -0.038** | -0.029* | -0.026** |
| | (0.010) | (0.017) | (0.015) | (0.013) |
| *N. of observations* | 20,620 | 756 | 935 | 1,101 |
| **Panel B. Low income** | | | | |
| Admission | -0.044** | -0.057* | -0.043* | -0.040* |
| | (0.020) | (0.030) | (0.026) | (0.023) |
| Enrollment | -0.053** | -0.066* | -0.050* | -0.046* |
| | (0.024) | (0.034) | (0.030) | (0.026) |
| *N. of observations* | 7,830 | 323 | 407 | 480 |
| **Panel C. High income** | | | | |
| Admission | -0.007 | 0.000 | -0.002 | -0.001 |
| | (0.009) | (0.003) | (0.002) | (0.002) |
| Enrollment | -0.009 | 0.000 | -0.002 | -0.001 |
| | (0.011) | (0.003) | (0.003) | (0.002) |
| *N. of observations* | 6,833 | 214 | 272 | 325 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution using alternative specifications. In column (1), estimates are obtained using LWR with a second-degree polynomial for the admission score and a triangular kernel. Bandwidth is selected using the Calonico, Cattaneo and Titiunik's (2014) procedure. In columns (2)-(4), SRD estimates are obtained by taking the mean difference between the next-to-last admitted applicants and the first non-admitted applicants in each program cohort; FRD estimates are obtained by dividing the SRD by the mean difference in the enrollment rate. Each column uses a different number of observations above and below the admission cutoff per program cohort. For example, column (2) compares the first four applicants above the cutoff with the first four applicants below the cutoff. Following de Chaisemartin and Behaghel (2020), we do not include the last admitted applicant in each program cohort. All samples exclude applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Table A8:** Effects of Admission and Enrollment on Criminal Prosecution, Controlling for Program-Cohort Fixed Effects

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.023*** | -0.015** | -0.011** | -0.011** | -0.005 | -0.012** |
| | (0.008) | (0.006) | (0.005) | (0.005) | (0.004) | (0.005) |
| Enrollment | -0.027*** | -0.018** | -0.013** | -0.014** | -0.006 | -0.015** |
| | (0.009) | (0.007) | (0.006) | (0.006) | (0.005) | (0.006) |
| *Baseline mean* | 0.035 | 0.020 | 0.016 | 0.016 | 0.010 | 0.019 |
| *N. of observations* | 20,620 | 20,620 | 20,620 | 20,620 | 20,620 | 20,620 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.040** | -0.030** | -0.016 | -0.015 | -0.006 | -0.015 |
| | (0.016) | (0.013) | (0.011) | (0.011) | (0.009) | (0.011) |
| Enrollment | -0.048** | -0.036** | -0.019 | -0.018 | -0.007 | -0.017 |
| | (0.019) | (0.015) | (0.013) | (0.013) | (0.011) | (0.013) |
| *Baseline mean* | 0.054 | 0.035 | 0.026 | 0.026 | 0.016 | 0.024 |
| *N. of observations* | 7,830 | 7,830 | 7,830 | 7,830 | 7,830 | 7,830 |
| **Panel C. High income** | | | | | | |
| Admission | -0.005 | 0.000 | -0.001 | -0.007 | -0.007** | -0.001 |
| | (0.008) | (0.003) | (0.003) | (0.005) | (0.004) | (0.006) |
| Enrollment | -0.006 | 0.000 | -0.001 | -0.009 | -0.009** | -0.001 |
| | (0.010) | (0.004) | (0.004) | (0.006) | (0.004) | (0.008) |
| *Baseline mean* | 0.009 | 0.000 | 0.001 | 0.008 | 0.007 | 0.006 |
| *N. of observations* | 6,833 | 6,833 | 6,833 | 6,833 | 6,833 | 6,833 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. All regressions control for program-cohort fixed effects. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Table A9:** Effects of Admission and Enrollment on Criminal Prosecution, Excluding Applicants Near the Admission Cutoff

| | Excluding admission scores within: | | | | | |
|---|---|---|---|---|---|---|
| | $(-.05, .05)$ | $(-.10, .10)$ | $(-.15, .15)$ | $(-.05, 0)$ | $(-.10, 0)$ | $(-.15, 0)$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.035*** | -0.042*** | -0.035*** | -0.034*** | -0.037*** | -0.033*** |
| | (0.010) | (0.012) | (0.012) | (0.009) | (0.009) | (0.009) |
| Enrollment | -0.041*** | -0.048*** | -0.041*** | -0.040*** | -0.043*** | -0.038*** |
| | (0.012) | (0.014) | (0.013) | (0.011) | (0.010) | (0.010) |
| *N. of observations* | 20,093 | 19,584 | 19,119 | 20,317 | 20,058 | 19,815 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.043* | -0.050 | -0.049 | -0.046** | -0.058** | -0.059** |
| | (0.023) | (0.031) | (0.033) | (0.020) | (0.025) | (0.023) |
| Enrollment | -0.052* | -0.059 | -0.057 | -0.055** | -0.069** | -0.069** |
| | (0.027) | (0.036) | (0.038) | (0.024) | (0.029) | (0.027) |
| *N. of observations* | 7,653 | 7,489 | 7,319 | 7,731 | 7,643 | 7,556 |
| **Panel C. High income** | | | | | | |
| Admission | -0.010 | -0.038** | -0.028 | -0.011 | -0.024* | -0.017 |
| | (0.012) | (0.018) | (0.019) | (0.011) | (0.015) | (0.015) |
| Enrollment | -0.013 | -0.043** | -0.036 | -0.014 | -0.029* | -0.020 |
| | (0.015) | (0.021) | (0.024) | (0.013) | (0.017) | (0.017) |
| *N. of observations* | 6,634 | 6,422 | 6,251 | 6,715 | 6,604 | 6,511 |

This table presents the SRD estimates for the effect of admission on the probability of criminal prosecution within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. In each column, the sample excludes applicants with standardized admission score within the indicated range. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Table A10:** Effects of Admission and Enrollment on the Type of Crime Among Formally Employed Individuals

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.029*** | -0.019** | -0.019*** | -0.010 | -0.009 | -0.018** |
| | (0.011) | (0.009) | (0.007) | (0.007) | (0.006) | (0.007) |
| Enrollment | -0.034*** | -0.023** | -0.022*** | -0.012 | -0.011 | -0.022** |
| | (0.013) | (0.010) | (0.008) | (0.009) | (0.007) | (0.009) |
| *Baseline mean* | 0.046 | 0.028 | 0.024 | 0.017 | 0.015 | 0.027 |
| *N. of observations* | 13,231 | 13,231 | 13,231 | 13,231 | 13,231 | 13,231 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.043* | -0.041** | -0.027* | -0.017 | -0.009 | -0.012 |
| | (0.022) | (0.017) | (0.014) | (0.015) | (0.012) | (0.015) |
| Enrollment | -0.053** | -0.050** | -0.033** | -0.021 | -0.011 | -0.015 |
| | (0.027) | (0.021) | (0.016) | (0.018) | (0.015) | (0.018) |
| *Baseline mean* | 0.067 | 0.049 | 0.040 | 0.033 | 0.021 | 0.025 |
| *N. of observations* | 5,634 | 5,634 | 5,634 | 5,634 | 5,634 | 5,634 |
| **Panel C. High income** | | | | | | |
| Admission | -0.013 | -0.002 | 0.000 | -0.010 | -0.013* | -0.005 |
| | (0.009) | (0.004) | (0.005) | (0.006) | (0.006) | (0.006) |
| Enrollment | -0.016 | -0.002 | 0.000 | -0.012 | -0.015* | -0.006 |
| | (0.010) | (0.004) | (0.005) | (0.008) | (0.008) | (0.007) |
| *Baseline mean* | 0.009 | 0.000 | 0.000 | 0.008 | 0.011 | 0.001 |
| *N. of observations* | 3,728 | 3,728 | 3,728 | 3,728 | 3,728 | 3,728 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample includes only applicants who were formally employed ten years after application and excludes those who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table A11:** Effects of Admission and Enrollment on Graduation from the Flagship University by Type of Program

| | Dependent variable: graduated at the flagship university within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | Share of low-income students | | | Share of students from private high schools | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Low income** | | | | | | |
| | 1st & 2nd quartiles | 3rd quartile | 4th quartile | 1st quartile | 2nd quartile | 3rd & 4th quartiles |
| Admission | 0.364*** | -0.115 | 0.397*** | 0.380*** | 0.046 | 0.418*** |
| | (0.089) | (0.236) | (0.075) | (0.073) | (0.137) | (0.116) |
| Enrollment | 0.488*** | -0.223 | 0.446*** | 0.435*** | 0.068 | 0.562*** |
| | (0.109) | (0.452) | (0.080) | (0.080) | (0.184) | (0.142) |
| *Baseline mean* | 0.201 | 0.355 | 0.237 | 0.243 | 0.226 | 0.244 |
| *N. of observations* | 2,559 | 729 | 2,346 | 2,581 | 1,479 | 1,574 |
| **Panel B. High income** | | | | | | |
| | 1st quartile | 2nd quartile | 3rd & 4th quartiles | 1st & 2nd quartiles | 3rd quartile | 4th quartile |
| Admission | 0.464*** | 0.339*** | 0.361*** | 0.400*** | 0.405*** | 0.331*** |
| | (0.112) | (0.101) | (0.082) | (0.085) | (0.114) | (0.096) |
| Enrollment | 0.536*** | 0.381*** | 0.430*** | 0.466*** | 0.461*** | 0.387*** |
| | (0.114) | (0.111) | (0.093) | (0.094) | (0.132) | (0.103) |
| *Baseline mean* | 0.359 | 0.336 | 0.315 | 0.280 | 0.203 | 0.444 |
| *N. of observations* | 1,046 | 1,122 | 1,560 | 1,299 | 861 | 1,568 |

This table presents the SRD estimates for admission effect and the FRD estimates for enrollment effect on the probability of graduating at the flagship university within 10 years following the application. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and were not formally employed ten years later. In each column, samples are split based on the characteristics of the program students apply. In columns (1)-(3), the split is at the quartiles of the share of low-income students admitted to the program. In columns (4)-(6), the split is at the quartiles of the share of admitted students who graduated from a private high school. SRDs and FRDs are estimated using triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. All regressions control for gender, cohort, and program fixed effects. Standard errors, clustered at student level, are in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10% levels, respectively.

**Table A12:** Effects of Admission and Enrollment on College Graduation by Type of Program

| | Dependent variable: graduated at any HE institution within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | Share of low-income students | | | Share of students from private high schools | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Low income** | | | | | | |
| | 1st & 2nd quartiles | 3rd quartile | 4th quartile | 1st quartile | 2nd quartile | 3rd & 4th quartiles |
| Admission | 0.086 | 0.357** | 0.077 | 0.110 | 0.038 | 0.087 |
| | (0.084) | (0.162) | (0.071) | (0.071) | (0.106) | (0.094) |
| Enrollment | 0.116 | 0.714** | 0.086 | 0.127 | 0.051 | 0.116 |
| | (0.111) | (0.312) | (0.079) | (0.081) | (0.137) | (0.126) |
| *Baseline mean* | 0.709 | 0.631 | 0.669 | 0.648 | 0.661 | 0.780 |
| *N. of observations* | 2,559 | 729 | 2,346 | 2,581 | 1,479 | 1,574 |
| **Panel B. High income** | | | | | | |
| | 1st quartile | 2nd quartile | 3rd & 4th quartiles | 1st & 2nd quartiles | 3rd quartile | 4th quartile |
| Admission | -0.080* | 0.009 | 0.085 | 0.101 | -0.060 | -0.034 |
| | (0.045) | (0.068) | (0.068) | (0.072) | (0.097) | (0.035) |
| Enrollment | -0.093* | 0.010 | 0.101 | 0.118 | -0.069 | -0.040 |
| | (0.053) | (0.076) | (0.081) | (0.085) | (0.110) | (0.042) |
| *Baseline mean* | 0.982 | 0.863 | 0.781 | 0.756 | 0.832 | 0.975 |
| *N. of observations* | 1,046 | 1,122 | 1,560 | 1,299 | 861 | 1,568 |

This table presents the SRD estimates for admission effect and the FRD estimates for enrollment effect on the probability of graduating at any college within 10 years following the application. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and were not formally employed ten years later. In each column, samples are split based on the characteristics of the program students apply. In columns (1)-(3), the split is at the quartiles of the share of low-income students admitted to the program. In columns (4)-(6), the split is at the quartiles of the share of admitted students who graduated from a private high school. SRDs and FRDs are estimated using triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. All regressions control for gender, cohort, and program fixed effects. Standard errors, clustered at student level, are in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10% levels, respectively.

**Table A13:** Effect of Admission on the Probability of Finding the Academic Degree

| | Dependent variable: degree found on the web | | |
|---|---|---|---|
| | | Share of students from private high schools | |
| | All | High | Low |
| | (1) | (2) | (3) |
| **Panel A. All sample** | | | |
| Admission | 0.033 | -0.020 | 0.104* |
| | (0.035) | (0.051) | (0.057) |
| *Baseline mean* | 0.366 | 0.355 | 0.394 |
| *N. of observations* | 11,255 | 5,728 | 5,527 |
| **Panel B. Low income** | | | |
| Admission | 0.072 | 0.071 | 0.064 |
| | (0.061) | (0.084) | (0.109) |
| *Baseline mean* | 0.338 | 0.347 | 0.364 |
| *N. of observations* | 4,013 | 2,139 | 1,874 |
| **Panel C. High income** | | | |
| Admission | -0.013 | -0.254*** | 0.171** |
| | (0.062) | (0.096) | (0.084) |
| *Baseline mean* | 0.412 | 0.430 | 0.410 |
| *N. of observations* | 3,906 | 1,586 | 2,320 |

This table presents the SRD estimates for the effect of admission on the probability of finding the future academic degree of applicants. The dependent variable is equal to one if the applicant's academic degree is found on *Escavador*, see Section A, and zero otherwise. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. It also excludes those who did graduate from college within ten years according to RAIS. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. In columns (2)-(3), we split the samples between programs with 'high' (above the median) and 'low' (below the median) share of students coming from private high schools. The median share is 0.72. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table A14:** Effect of Admission on Civil Prosecution by Type of Study Program

| | Dependent variable (within 10 years after application) | | | | | |
|---|---|---|---|---|---|---|
| | Divorce trial | | Collection lawsuit | | Other civil procedure | |
| | Share of low-income students | | | | | |
| | High | Low | High | Low | High | Low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.002 | -0.003 | 0.010 | -0.014 | 0.046* | -0.024 |
| | (0.005) | (0.005) | (0.022) | (0.020) | (0.025) | (0.023) |
| *Baseline mean* | 0.005 | 0.009 | 0.080 | 0.052 | 0.115 | 0.092 |
| *N. of observations* | 10,472 | 10,148 | 10,472 | 10,148 | 10,472 | 10,148 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.012 | 0.000 | -0.003 | 0.008 | 0.059 | 0.026 |
| | (0.011) | (0.016) | (0.040) | (0.044) | (0.048) | (0.048) |
| *Baseline mean* | 0.013 | 0.016 | 0.114 | 0.078 | 0.161 | 0.093 |
| *N. of observations* | 4,087 | 3,743 | 4,087 | 3,743 | 4,087 | 3,743 |
| **Panel C. High income** | | | | | | |
| Admission | 0.008 | -0.005 | 0.041 | -0.026 | 0.069* | -0.018 |
| | (0.006) | (0.004) | (0.029) | (0.017) | (0.036) | (0.028) |
| *Baseline mean* | -0.002 | 0.004 | 0.023 | 0.016 | 0.049 | 0.063 |
| *N. of observations* | 2,835 | 3,998 | 2,835 | 3,998 | 2,835 | 3,998 |

This table presents the SRD estimates for the effect of admission on the probabilities of being in a divorce trial, in columns (1)-(2), sued for non-payment, in columns (3)-(4), and prosecuted in another type of civil case, in columns (5)-(6), within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, and were already in college at the time of the admission exam. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. In columns (1)-(6), we split the samples between programs with 'high' (above the median) and 'low' (below the median) share of low-income students. SRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.

**Table A15:** Effects of Admission and Enrollment on Criminal Prosecution Excluding Applicants to the Law Program

| | Dependent variable: criminally prosecuted within 10 years | | | | | |
|---|---|---|---|---|---|---|
| | All crimes | Violent crimes | Property crimes | Against public interest | Traffic-related crimes | Unclassif. crimes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All sample** | | | | | | |
| Admission | -0.025*** | -0.017*** | -0.012** | -0.012** | -0.005 | -0.014** |
| | (0.008) | (0.006) | (0.005) | (0.006) | (0.004) | (0.006) |
| Enrollment | -0.030*** | -0.020*** | -0.015** | -0.014** | -0.006 | -0.016** |
| | (0.010) | (0.008) | (0.006) | (0.007) | (0.005) | (0.007) |
| *Baseline mean* | 0.038 | 0.023 | 0.017 | 0.017 | 0.010 | 0.021 |
| *N. of observations* | 18,525 | 18,525 | 18,525 | 18,525 | 18,525 | 18,525 |
| **Panel B. Low income** | | | | | | |
| Admission | -0.044** | -0.034** | -0.018 | -0.015 | -0.008 | -0.015 |
| | (0.017) | (0.014) | (0.011) | (0.011) | (0.010) | (0.012) |
| Enrollment | -0.053*** | -0.040** | -0.021 | -0.018 | -0.009 | -0.018 |
| | (0.020) | (0.016) | (0.013) | (0.013) | (0.011) | (0.014) |
| *Baseline mean* | 0.059 | 0.038 | 0.029 | 0.029 | 0.018 | 0.025 |
| *N. of observations* | 7,358 | 7,358 | 7,358 | 7,358 | 7,358 | 7,358 |
| **Panel C. High income** | | | | | | |
| Admission | -0.007 | -0.001 | 0.001 | -0.009 | -0.004 | -0.002 |
| | (0.009) | (0.003) | (0.002) | (0.006) | (0.004) | (0.007) |
| Enrollment | -0.008 | -0.001 | 0.002 | -0.011 | -0.005 | -0.003 |
| | (0.011) | (0.004) | (0.002) | (0.007) | (0.004) | (0.009) |
| *Baseline mean* | 0.011 | 0.000 | -0.002 | 0.008 | 0.004 | 0.007 |
| *N. of observations* | 5,761 | 5,761 | 5,761 | 5,761 | 5,761 | 5,761 |

This table presents the SRD and FRD estimates for the effect of admission and enrollment, respectively, on probability of criminal prosecution within ten years following the application to the university. The sample excludes applicants who did not pass to the second round of the admission exam, were older than 30 years, were already in college at the time of the admission exam, and applied to the study program in Law. 'Low income' are applicants with household income below 1,000 BRL/month. 'High income' are applicants with household income above 2,000 BRL/month. Each column presents the effect on a different type of crime. SRDs and FRDs are estimated using a triangular kernel with bandwidth selection based on Calonico, Cattaneo and Titiunik's (2014) procedure. Robust standard errors clustered at student level are in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. 'Baseline mean' is the predicted outcome just below the admission cutoff.