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Do disadvantaged students benefit from attending classes with more skilled colleagues?

Evidence from a top university in Brazil

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Abstract: Peers play an essential role in cognitive and non-cognitive skills formation. Ordinal rank may also change incentives and environment, impacting students' efforts. Using two rich administrative data sets and a rule of admission at one top university in Brazil, we apply a regression discontinuity design to study the effect of class allocation on academic performance and labour market outcomes. The rule creates two potential effects on students: peer and ranking effects. The last student of the first class will have higher-ability peers, but at the same time will have a lower ordinal rank than the first student of the second class. These effects usually play in different directions. The rich data also allows conducting all the analyses separately for affirmative action students and regular students. The main results suggest that affirmative action students, a group of disadvantaged Black and mixed-race students from low-income families and with lower levels of education, are the most negatively impacted by being the last student of the first class. They have a lower GPA in the first semester, in the first year, and when they graduate. They also have a higher number of failures. Students in STEM majors drive results. However, the class allocation has no impact on employment and income.

Key words: affirmative action, peer effect, ranking effect, Brazil, education

JEL classification: I24, I25, I28, J15

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1 Introduction

Peers play an important role in cognitive and non-cognitive skills formation. The extensive literature on the topic shows evidence of a positive relationship in elementary education (Hoxby 2000; Rao 2019), high school (Anelli and Peri 2017; Eisenkopf 2010; Sund 2009), and college (Ribas et al. 2020). However, there is also evidence that peers can be harmful (Bursztyn et al. 2019; Bursztyn and Jensen 2015), and the negative effects stronger when students are not at the top of the ability distribution (Booij et al. 2016). In other words, conditional on students' rank, better peers can reduce academic success.

Other studies have shown that ordinal rank can explain academic success (Dasgupta et al. 2020; Elsner and Isphording 2016; Elsner et al. 2021; Murphy and Weinhardt 2020; Zeidner and Schleyer 1999). The main explanation is that students with higher ability in a low-ability group may have a misconception about their absolute ability and thus invest more in their education. This phenomenon is known as the 'big fish in a small pond' effect (Zeidner and Schleyer 1999). The ordinal rank can affect students' achievement through other channels. First, students' social networks can be more supportive, depending on their rank. Second, students with a higher rank can be more motivated and self-confident (Elsner and Isphording 2016). Therefore, a student who is the last in her class's rank distribution can benefit from better peers or be armed by subjective factors related to the rank.

In this paper we leverage a rule of class assignment in one top university in Brazil to study class composition's effect on academic and labour market outcomes. In most of the majors, first-year students can be assigned to one of two possible groups based on their position in the admission exam rank and their group. The 50 per cent best-ranked students went to the first-semester group, which starts between February and March, and the remainder went to the second-semester group, which starts between July and August. The rank is conditional on the students' group, generating a specific rank for students who benefited from affirmative action policies and a specific rank for the students who did not (regular). The class composition respects the affirmative action rule that reserves 45 per cent of the slots for each course for former public high-school students from low-income families.[1]

All students must take a unique entrance exam to be selected to attend the Federal University of Bahia (UFBA). After the exam, a rank is created. The students cannot choose their starting semester, regardless of their group or score in the entrance exam. The assignment rule based on the entrance exam score allows us to use a sharp regression discontinuity design (RDD) to evaluate the class composition impact on students' grade point average (GPA) (in the beginning and end of the course), dropout, failures, graduation in time, employment, and income. The UFBA rule implies that students were allocated to different classes with different average abilities and different classmates. The students in each semester had different peers who could improve or reduce their performance. Within classes, the last student of the first class has a lower absolute rank than the first student of the second class.

We use two rich administrative data sets that comprise 17,089 students who enrolled at UFBA between 2006 and 2012.[2] We use this period because 2005 was the first year of the affirmative action policy, but there was a big strike at the end of 2004 that made the university cancel the first semester of 2005. We restrict our sample to 2012 because UFBA changed the selection process after this year and we do not have access to the information about students' score in the admission exam. For the students who graduated, we merge their information with their labour market characteristics using the labour market

[1] There is much evidence that public high schools are of worse quality than private high schools in Brazil, with students performing worse in standard exams such as PISA (https://brazilian.report/society/2017/11/06/education-brazil-staggering-inequality/).

[2] UFBA is the oldest university in Brazil, one of the top ten universities in the country, and the most prominent university in the Northeast region.

administrative registers from the Ministry of Economy of Brazil, which has identified information for all Brazilian workers with a formal written contract. We also merge the data sets using the Brazilian social security number (CPF). Thus, we are able to look at former students' employment status and income between one and four years after graduation.

The main findings suggest that being among the last of the first class is worse than being among the first of the second class for affirmative action students. Our sample size also allows performing heterogeneous analysis by STEM (science, technology, engineering, and medicine) and non-STEM majors. Being the last affirmative action student of the first class negatively impacts the average GPA in the first year by –4.16 per cent, while this effect for STEM majors is –10.7 per cent. Our hypothesis is that this finding can be explained by the fact that students from disadvantaged families have lower ability in maths- and science-related subjects. We further explored these findings by looking at specific subjects in each group. As expected, the results are much higher for maths-related subjects. Being among the last affirmative action students of the first class reduces the calculus' grades by –2.9 points on a 0–10 scale, a 29 per cent reduction or a 50 per cent reduction when compared to the control group mean.

The findings suggest that better peers could negatively impact the learning of the students through a peer pressure mechanism Bursztyn et al. (2019), or that better peers can harm individuals if they are not at the top of the ability distribution (Booij et al. 2016). On the other side, it could be that the better ordinal rank effect can positively affect the efforts of the best students of the second class. Unfortunately, the regression discontinuity setup does not allow us to disentangle which mechanisms are most important in the study. However, to try to shed light on whether the effects are driven by peers or ordinal rank, we estimate a model based on Elsner and Isphording (2016). The estimates suggest that ordinal rank has a stronger effect than peers in explaining the GPA at UFBA.

Finally, we also estimate the effect of the class allocation on the probability of being employed in the formal market after graduation, and on incomes. Most of the results have no statistical significance, and the signals are mixed.

This paper makes at least four contributions to the literature. First, there is a large literature of disadvantaged students entering top colleges, suggesting no clear evidence of whether they benefit or not, with some studies pointing out that there is no mismatch (Bagde et al. 2016; Dale and Krueger 2014) and others finding that the mismatch does happen (Arcidiacono 2005; Arcidiacono and Lovenheim 2016). The mechanisms that explain these results are still unclear, and some authors suggest that students could have a prior misconception about the major characteristics and their abilities. This paper shows that the quality of peers and the student's absolute ordinal rank may shed light on these literature findings.

Second, to the best of our knowledge, this is the first paper to study the effect of class composition among affirmative action and regular students at the college and university levels. Additionally, our analysis also breaks new ground by looking to a representative and respected university in a low- to middle-income country. Prior studies have addressed these matters separately, with some papers focusing on class composition among high- and low-ability students (Ribas et al. 2020) and others focusing on the class composition of minorities in elementary education (Rao 2019).

The third contribution relates to the impact of class composition on labour market outcomes. Although there is solid evidence about the impact of class composition on academic outcomes, little is known about the labour market effects. Fourth, we also contribute to the growing evidence of the effect of the ordinal rank in the explanation of academic achievement, but which is still concentrated in developed countries (Dasgupta et al. 2020; Elsner and Isphording 2016; Elsner et al. 2021; Murphy and Weinhardt 2020).

2 Institutional background

UFBA was created in 1808 as the first university in Brazil. Nowadays, UFBA is one of the largest higher education institutions in Brazil, both in terms of structure and students. Moreover, it is the biggest university in the Northeast region.[3] UFBA is entirely tuition-free. Therefore, this is the best option, and sometimes the only option, for students from less advantaged families to access college. To enter UFBA, students had to do a unique exam, held once per year, called the vestibular. The vestibular had questions about Portuguese grammar and reading, maths, physics, chemistry, geography, biology, foreign language (English or Spanish), history, and philosophy. After the exams, students were ranked and then selected depending on the number of available places for each chosen major. Students need to choose their major before the exam. In this case, they don't know the minimum score to be selected.[4]

UFBA was the second university to adopt affirmative action policies for admissions, but the first to offer 45 per cent of the slots. The policy, created in 2004, aimed to offer the opportunity to enter the state flagship university to students who only have access to primary education of lower quality, and most of whom are poor. The eligibility criteria is being a former student from a public institution during high-school education.[5] Also, 85 per cent of the enrolled students must be Black or mixed race.

Until 2013, 23 courses selected students into two periods. The best 50 per cent of students at the vestibular were selected to start at the university in March, and the other 50 per cent would start in August. The students could not choose which semester they wanted to start; this allocation was done only by respecting each vestibular major ranking. If a student was selected for the first semester and chose not to start at UFBA in that semester, she needed to do the vestibular again the following year. The selection process was carried out independently for each group of students, obeying the descending order of the overall score calculated from the students' performance in the vestibular. For example, if the course has 100 available slots for the first semester and 100 for the second semester, 45 of these slots in each semester will be filled by Quota applicants. This policy of UFBA is of importance since the university is in the state of Bahia, where, according to PNAD data,[6] 83 per cent of the population is Black or mixed race, the highest percentage among all Brazilian states.

3 Data

We use two rich administrative data sets in this study, with the registries matched using a unique identifier: the CPF (*Cadastro de Pessoas Físicas*), a nine-digit individual taxpayer identification number.

UFBA: academic performance. The administrative records are composed of two data sets, one comprising the socioeconomic questionnaire held on vestibular day and containing the grades of all the students who took the exam, and another containing the scholastic history of the students that enrolled

[3] In 2017, UFBA had 105 undergraduate courses, 136 postgraduate courses (82 masters and 54 PhDs), and 42 postgraduate specialization courses. In that same year, the UFBA budget was US$413,446,423.98, and it offered 8,875 vacancies to new students that did the vestibular in 2016.

[4] After 2013 the vestibular was replaced by a national selection process called SISU (*Sistema de Seleção Unificada*). Since SISU was adopted, UFBA stopped collecting information about students' grades and socioeconomic characteristics; therefore, we work only with students who did the vestibular up to 2013.

[5] https://brazilian.report/society/2017/11/06/education-brazil-staggering-inequality/.

[6] Brazilian Annual Household Survey, conducted by the Brazilian Institute of Statistics (IBGE).

at UFBA. The complete sample has a total of 17,568 students, 6,768 Quotas and 10,800 non-Quotas, who after the vestibular completed the registration process to enrol at the university.

The administrative records of UFBA provide detailed information on students' grades in each subject, year of graduation, and failures. We use this information to calculate the GPA at the beginning and at the end of the course, dropouts, graduation within a certain time, and failures.

Specifically for the GPA, we calculate three indicators: (1) the weighted-average grade in the first semester—this variable could be interpreted as the GPA of the first semester;[7] (2) the weighted-average grade in the first year at the university; and (3) the coefficient of performance (GPA) that is measured by the university at the end of the course. This measure is the weighted-average grade for the entire major. With these three variables we intend to measure student performance on a scale of 0 to 10 at different moments over the course. This measure allows us to compare the students as a freshman and as a bachelor's candidate.

RAIS: employment and income. The labour market outcomes stem from RAIS (*Relação Anual de Informações Sociais*), a matched employee–employer data set from Brazil's Ministry of Economy. The RAIS data set has information on each formal worker at each plant in Brazil, as all establishments in Brazil are legally required to submit information to RAIS. We use yearly information for the period 2008–17. We construct a set of dummies of formal employment, which equals 1 if the individual is formally employed in December of each year and 0 otherwise. We also collect information on earnings in December of each year.[8] Note that RAIS has information only for workers in the formal labour sector.

3.1 Descriptive statistics

Table 1 shows the variables in our data set. Panel A presents the statistics for the whole sample, and Panel B presents only the statistics for those around the cut-off in the RDD design. This table shows that for both affirmative action and regular students the explanatory covariates are well balanced. However, for the vestibular score and the outcome variables it is possible to see that they are balanced only around the cut-off.[9]

The vestibular score average is higher in the first class, for both affirmative action and regular students, showing that students in these classes have peers with better skills. The number also suggests that regular students need a higher score in the vestibular exam to enter the university. The average score of regular students in the second class is higher than the average score of the affirmative action students in the first class. This is simple evidence that affirmative action plays an important role in providing access for disadvantaged students to enter UFBA.

[7] The grades are weighted by the total hours in each subject.

[8] For a few individuals who have two or more jobs, we considered only the job with higher earnings.

[9] Although we show the age distribution in this table we do not use it in the regression because this variable has a large amount of missing information for a considerable percentage of the sample.

Table 1: Descriptive statistics

	Affirmative action students				Regular students			
	First class	Second class	Mean difference [*p*-value]	Obs.	First class	Second class	Mean difference [*p*-value]	Obs.
Panel A: All students								
Age	21.30	21.60	–0.30	4,329	19.25	19.40	–0.15	6,676
	(5.4)	(5.76)	[0.07]		(3.35)	(3.59)	[0.08]	
Sex	0.48	0.42	0.06	5,565	0.45	0.45	0.00	8,958
	(0.49)	(0.49)	[0.00]		(0.497)	(0.497)	[0.98]	
Share of students in STEM	0.23	0.22	0.01	5,565	0.23	0.23	0.00	8,958
	(0.42)	(0.41)	[0.36]		(0.42)	(0.42)	[0.85]	
Vestibular score	13,291	11,159	2,132	5,565	15,420	12,899	2,521	8,958
	(1,469)	(2,516)	[0.00]		(1,795)	(3,410)	[0.00]	
First semester GPA	6.9	6.5	0.4	5,214	7.5	7.1	0.4	8,524
	(1.5)	(1.46)	[0.00]		(1.36)	(1.37)	[0.00]	
First year GPA	6.8	6.5	0.3	5,265	7.4	7.1	0.3	8,558
	(1.42)	(1.47)	[0.00]		(1.33)	(1.37)	[0.00]	
Final GPA	6.0	5.8	0.2	5,514	6.7	6.3	0.4	8,894
	(2.20)	(2.05)	[0.00]		(2.14)	(2.11)	[0.00]	
Failures	5.49	8.11	–2.62	5,565	2.72	4.21	–1.49	8,958
	(7.68)	(9.68)	[0.00]		(4.90)	(6.44)	[0.00]	
Graduation in time	0.83	0.80	0.03	5,565	0.84	0.79	0.05	8,958
	(0.38)	(0.40)	[0.02]		(0.36)	(0.40)	[0.00]	
Dropout	0.44	0.48	–0.04	5,565	0.36	0.42	–0.06	8,958
	(0.5)	(0.5)	[0.01]		(0.48)	(0.49)	[0.00]	
Employment after graduation	0.3	0.29	0.01	38,638	0.242	0.238	0.004	67,627
	(0.46)	(0.46)	[0.15]		(0.43)	(0.43)	[0.22]	
Income after graduation	3,409.4	3,199.7	209.7	15,778	4,479.6	4,056.9	422.8	23,123
	(3,669)	(3,318)	[0.00]		(5,048)	(4,071)	[0.00]	
Panel B: Students around the cut-off								
Age	21.52	21.65	–0.13	1,977	19.53	19.30	0.23	2,712
	(5.4)	(5.8)	[0.63]		(3.97)	(3.44)	[0.06]	
Sex	0.47	0.44	0.03	2,415	0.44	0.44	0.00	3,612
	(0.5)	(0.5)	[0.16]		(0.5)	(0.5)	[0.90]	
Share of students in STEM	0.24	0.21	0.03	2,415	0.21	0.23	–0.02	3,612
	(0.42)	(0.40)	[0.07]		(0.41)	(0.42)	[0.30]	
Vestibular score	12,620	11,935	685	2,415	14,751	14,025	726	3,612
	(1,159)	(1,766)	[0.00]		(1,742)	(2,366)	[0.00]	
First semester GPA	6.68	6.54	0.14	2,289	7.28	7.17	–0.11	3,483
	(1.46)	(1.48)	[0.03]		(1.41)	(1.33)	[0.02]	
First year GPA	6.57	6.55	0.02	2,306	7.13	7.17	–0.04	3,496
	(1.35)	(1.48)	[0.77]		(1.32)	(1.33)	[0.37]	
Final GPA	5.91	5.87	0.04	2,402	6.48	6.43	0.05	3,593
	(2.07)	(2.03)	[0.63]		(2.06)	(2.05)	[0.42]	
Failures	7.04	7.50	–0.46	2,415	3.64	3.88	0.24	3,612
	(8.87)	(9.06)	[0.21]		(5.76)	(6.00)	[0.24]	
Graduation in time	0.82	0.82	0.00	2,415	0.83	0.80	0.03	3,612
	(0.38)	(0.38)	[0.99]		(0.38)	(0.40)	[0.03]	
Dropout	0.42	0.46	–0.04	2,415	0.37	0.41	–0.04	3,612
	(0.49)	(0.5)	[0.03]		(0.48)	(0.49)	[0.01]	
Employment after graduation	0.29	0.29	0.00	9,683	0.25	0.24	0.01	15,544
	(0.45)	(0.45)	[0.81]		(0.43)	(0.42)	[0.22]	
Income after graduation	3,028.4	3,018.6	9.8	3,827	3,938.5	4,287.7	–349.1	5,385
	(3,059)	(2,944)	[0.92]		(4,563)	(4,313)	[0.00]	

Source: authors' calculations based on UFBA and RAIS data.

4 Empirical strategy

4.1 Method

We use a sharp discontinuity regression to estimate the effect of class assignment on educational and labour market outcomes. We assume that, for each course and affirmative action status, the last student joining the first class is similar to the first student of the second class. These students need to enrol in the same subjects and study in the same buildings. The only difference between them is their classmates, with the classmates in the first class having better vestibular scores. The students also have different ordinal ranks depending on which class they enrol in. It is important to point out that all estimates are done separately between affirmative action and regular students, because each group has different thresholds.

In our setting, the cut-off is the score of the last student i of group g that entered during the first class (beginning in March) in each year t for major c. As in Francis-Tan and Tannuri-Pianto (2018), the running variable is the normalized score calculated as $NS_{igtc} = \frac{(S_{igtc} - C_{tgc})}{SD_{tgc}}$, where S_{igtc} is the score of student i in the admission process; C is the score of the last student of group g classified for the first semester of major c and year t (cut-off); and SD is the standard deviation of the score for group g, course c, and year t. In particular, we estimate the nonparametric local linear models of the form:

$$Y_{igc} = \beta_0 + \beta_1 r_{igtc} + \beta_2 A_i + \beta_3 r_{igtc} * A_i + \beta_4 sex + \gamma_c + \rho_t + \varepsilon_{igc} \quad (1)$$

where Y_{igc} is an outcome for student i in group g and major c. $A_i = 1\{NS_{igtc} \geq 0\}$, with positive values meaning those students with normalized score equal or above the minimum to be in the first class. We add the major fixed effect, γ_c, and the year in which they started the major, ρ_t, to account for possible year-related unobserved factors. We also use a dummy covariate of sex because the class composition can impact men and women in different ways (Ribas et al. 2020). Calonico et al. (2019) and Frölich and Huber (2019) showed that the inclusion of pre-treatment covariates can increase the precision of the estimates. We use a triangular kernel function for weighting the observations and we apply the estimator and the bandwidth selection proposed by Calonico et al. (2014).[10] We report robust estimates in the text.[11]

The main underlying hypothesis is that students cannot manipulate their entrance exam scores around the cut-off. Because each student needs to choose the major before the exam, they do not know the minimum score to be in the first class. The minimum score depends also on the other students' efforts. In addition, Table A1 in Appendix A shows the coefficients of the manipulation test proposed by Cattaneo et al. (2020). The results suggest that there is no evidence of manipulation around the cut-off.

5 Results

We divide the results into three parts. First, we provide the results on academic performance (GPA, dropouts, graduation in time, and failures), and the heterogeneity analyses by STEM versus non-STEM. Second, we perform the analyses at the subject level and look at the difference between the effects of rank and peers. Finally, in the third part, we provide the results on employment and income.

In Appendix A we present in Figure A1 the relationship between the academic outcomes and the running variable. In Figure A2 we show those Figures for labour market outcomes. These figures suggests that

[10] Tables A2 to A5 in Appendix A present estimates using different bandwidth selection methods.

[11] Tables A6 and A7 show the results using conventional and bias-corrected methods.

there is discontinuity for affirmative action students in STEM majors for most of the academic outcomes, but not for the labour market outcomes. The corresponding relationships for the regular students are presented in Figures A3 and A4.

5.1 Academic performance

Table 2 presents the main baseline results of the impact of being among the last student of the first class. The results are always presented separately for affirmative action and regular students. Column 1 shows that for affirmative action students, being among the last of the first class reduces the average grade in the first year by 4.16 per cent, a 6.4 per cent increase compared to the control group average. The probability of failures also reduces by 1.5 percentage points during the course, which implies a 25 per cent reduction compared to the control group average. Column 4 shows that the effect on regular students goes in the opposite direction for grades, with the last student of the first class having a better GPA in the first semester (2.8 per cent), and in the final of the course (3.9 per cent). They also have a lower probability of dropout and a higher probability of graduating on time.

Table 2: Baseline effects of class allocation

Dependent variables	Affirmative action students			Regular students		
	Everyone (1)	STEM (2)	Not STEM (3)	Everyone (4)	STEM (5)	Not STEM (6)
First semester GPA	–0.199	–0.784***	0.030	0.280**	–0.109	0.382**
	(0.146)	(0.235)	(0.133)	(0.134)	(0.253)	(0.174)
First year GPA	–0.416***	–1.079***	–0.120	0.049	–0.371	0.147
	(0.136)	(0.227)	(0.109)	(0.127)	(0.228)	(0.164)
Final GPA	–0.123	–0.673	0.031	0.390**	–0.046	0.472**
	(0.181)	(0.462)	(0.202)	(0.180)	(0.394)	(0.211)
Dropout	–0.032	–0.024	–0.044	–0.071**	–0.058	–0.068*
	(0.037)	(0.121)	(0.042)	(0.031)	(0.069)	(0.041)
Failures	1.543***	1.758*	1.288*	0.493	1.438**	0.045
	(0.578)	(1.104)	(0.677)	(0.347)	(0.658)	(0.475)
Graduation in time	0.005	0.117	–0.007	0.038*	0.108***	0.013
	(0.028)	(0.110)	(0.028)	(0.021)	(0.033)	(0.020)
Observations	5,565	1,250	4,315	8,915	2,124	6,791

Note: this table presents the estimated sharp regression discontinuity (RD) at the first class cut-off. All models estimated in this table were controlled by gender, course fixed effects, and year of entry fixed effects. RDs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for entrance score is selected based on Calonico et al.'s (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significant at the 1, 5, and 10 per cent levels, respectively.

Source: authors' calculations based on UFBA and RAIS data.

Columns 2 and 3 show that affirmative action students in STEM courses mainly drive the effects. Affirmative action students are strongly armed by being the 'little fish in a big pond' in STEM courses. Entering UFBA as the last student of the first class reduces their average grades in the first semester by 7.8 per cent, and their first-year average grades by 10.7 per cent. This represents a reduction of 13.8 per cent and 18.9 per cent compared to the control group average. However, there are no differences in the final GPA. They also have 1.9 percentage points more chance to fail in subjects than the students in the second class, which is a reduction of 15 per cent compared to the control group average.

Columns 5 and 6 present the results for regular students in STEM and non-STEM courses. The results are mixed, with the last of the first class students in STEM courses having a higher probability of failures and a higher probability of graduating in time. The last of the first class students in non-STEM courses have better grades in the first semester and at the end of the course.

The results present two major points. The first is that the impact of class allocation is larger for affirmative action students in STEM courses when looking at the GPA. However, the impacts reduce and are not statistically significant at the end of the course. Therefore, the effects of the peers and the ordinal rank diminishes through time for this group. A lower GPA also implies a higher number of failures.

Second, regular students do better even when they are the last of the first class. The difference in GPA is much smaller than in the previous case, but they have a lower probability of dropout and a higher probability of graduation in time. Unfortunately, the data do not allow us to investigate these results further. However, the anecdotal evidence suggests that when high-ability regular students go to the second class (which starts in August), they have a higher probability of starting a major in a private university in the first semester. Regular students come from families with higher incomes. Therefore, some of them can choose not to continue studying at UFBA, increasing the dropout rates. Some of them also choose to do the UFBA major slower, while focusing on their major at the private university.

5.2 Further analyses: mechanism

Results at the subject level

The previous section showed that being among the last affirmative action students in the first class reduces students' academic achievement and that the effect is much greater for students in STEM majors. Our main hypothesis is that affirmative action students have worse maths-related abilities before college. We investigated this by using a sample of enrolled students in different subjects in the first semester.

We select all subjects with more than 300 enrolled students in our sample, allowing for the optimal bandwidth calculation. The results presented in Table 3 support our prior. The effects for the subject calculus are much higher than for other subjects. The results are also much stronger than those observed for the GPA in the first semester, first year, and at the end of the major. More specifically, being among the last affirmative action students in the first class reduces their grades by 3.6 points on a scale between 0 and 10. This means a grade reduction of 50 per cent compared to the average grade of the best affirmative action students in the second class.

The analysis at the subject level also allows doing another exercise. One concern about the results is that professors with more experience at UFBA could know that students in the first class have better vestibular scores. Therefore, they could reduce the level of the exams for the second class. We identify only teachers with a temporary contract in the data set to show a low probability of this scenario. Then, we estimate the RDD only for classes with temporary teachers.

Temporary teachers are selected in very particular cases. For example, if a professor receives a scholarship to stay for one year working as a visiting researcher in one university abroad, her department can request a temporary teacher. The contract is six months long and can be extended to a maximum of four semesters. Therefore, temporary teachers usually don't know about the university rules, and some of them taught only one semester. In columns 2 and 4 of Table 3, we show that the results for this sample only do not change compared to the sample with all professors. This result suggests that teachers do not change classes' difficulty to benefit the students who enter in the second semester.

Table 3: Class allocation effects on subjects grades

Subjects	Affirmative action students		Regular students	
	All classes	Classes with only temporary teacher	All classes	Classes with only temporary teacher
	(1)	(2)	(3)	(4)
Calculus A	–3.592***	–3.568***	–0.112	0.382
	(0.865)	(0.842)	(0.459)	(0.520)
Observations	863	696	1,619	1,343
Microbiology	–0.563*	–0.661	–0.049	–0.110
	(0.288)	(0.457)	(0.214)	(0.463)
Observations	972	455	1,558	632
Introduction to biology	–0.424	0.690	–0.054	0.901
	(0.626)	(0.933)	(0.400)	(0.873)
Observations	448	97	612	175
Civil engineering	0.282	0.225	0.064	0.312
	(0.463)	(0.367)	(0.376)	(0.367)
Observations	408	198	679	316
Anatomy	–0.130	–0.482	–0.088	0.072
	(0.397)	(0.627)	(0.259)	(0.373)
Observations	912	588	1,289	672

Note: this table presents the estimated sharp RD at the first class cut-off. All models estimated in this table were controlled by gender, course fixed effects and year of entry fixed effects. RDs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for entrance score is selected based on Calonico et al.'s (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significance at the 1, 5, and 10 per cent levels, respectively.

Source: authors' calculations based on UFBA and RAIS data.

Peers versus ordinal rank

Although the findings are already an important contribution to the literature, it would also be useful to understand whether the results are driven by peers or rank. Unfortunately, the RDD does not allow decomposing the effects among ordinal rank and peers. However, it is an important part of the explanation of the findings. To shed light on possible mechanisms underlying the effects, we estimate a model based on Elsner and Isphording (2016), as shown in Equation 2. The main limitation compared to the previous section is that we cannot compare only among the last of the first class and the first of the second class.

$$\begin{aligned} Y_{igc} = \beta_0 + \beta_1 sex_i + \beta_2 AA + \beta_3 Fst.Semester + \beta_4 Peers + \beta_5 Rank + \\ \beta_6 Rank * AA + \beta_7 Peers * AA + \gamma_s + \theta_c + \varepsilon_{igc} \end{aligned} \tag{2}$$

β_4 is the impact of peers on the outcomes. *Peers* was measured as the averaged entrance exam score of the class the student started in the university. Classes in which the enrolled candidates had better scores in the entrance exam will have higher values. β_5 measures the impact of the ordinal rank among their group. This variable is adapted from Elsner and Isphording (2016) and created as:

$$Rank = 1 - \left[\frac{\text{Absolute Rank} - 1}{\text{No. students in major } c \text{ and group } g - 1} \right]$$

Rank varies between 0 and 1. Higher values refer to students with the better rank among those in their class and group in the entrance exam test. β_6 measures the impact of rank for the affirmative action students. Finally, β_7 measures the effect of peers for affirmative action students. We also control for course fixed effects, θ_c, and entry semester fixed effects, γ_s.

Table 4 shows the results. The findings suggest that peers do not play an important role in explaining academic success. However, the ordinal rank does have an important and strong effect. The results also show that the rank effect is stronger for affirmative action students. It is important to point out that these are correlations based on an ordinary least squares (OLS) model.

Table 4: Effects of peers and ordinal rank on academic outcomes

Outcomes	GPA first sem.		GPA first year		Final GPA	
	(1)	(2)	(3)	(4)	(5)	(6)
Sex	–0.258***	–0.252***	–0.268***	–0.261***	–0.668***	–0.648***
	(0.0301)	(0.0294)	(0.0300)	(0.0293)	(0.0598)	(0.0593)
Affirmative action	–0.612***	0.447	–0.596***	0.628	–0.548***	2.491**
	(0.0743)	(0.584)	(0.0710)	(0.529)	(0.122)	(0.907)
First sem.	0.0234	0.0267	–0.103	–0.0987	–0.108	–0.101
	(0.0708)	(0.0710)	(0.0700)	(0.0705)	(0.0717)	(0.0737)
Peers	0.000357***	0.000389***	0.000345***	0.000381***	0.000415***	0.000500***
	(0.0000402)	(0.0000387)	(0.0000377)	(0.0000354)	(0.0000697)	(0.0000764)
Rank	0.682***	0.590***	0.670***	0.580***	0.528***	0.498***
	(0.0555)	(0.0727)	(0.0507)	(0.0664)	(0.0782)	(0.0853)
Rank*aff. action		0.222***		0.215**		0.0660
		(0.0778)		(0.0785)		(0.129)
Peers*Aff. Action		–0.0000850*		–0.0000966**		–0.000223***
		(0.0000415)		(0.0000376)		(0.0000670)
Constant	2.163***	1.772***	2.336***	1.881***	0.841	–0.319
	(0.519)	(0.503)	(0.486)	(0.455)	(0.923)	(1.010)
Observations	17,525	17,525	17,647	17,647	18,440	18,440

Note: standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Source: authors' calculations based on UFBA and RAIS data.

5.3 Employment and income

This subsection provides the estimates of the impact of class allocation on employment and income after graduation. Table 5 shows the results for employment in columns 1–3 and for income in columns 4–6. The number of observations in each row is different because there are no observations two, three, or four years after graduation for students who graduate later. For example, for a student who graduated in 2012, we can observe him for four years after graduation (2013–16). On the other hand, for a student who graduated in 2015, it is possible to follow only in 2016 and 2017.

As can be seen, there is no pattern in the effect of class allocation for either affirmative action or regular students. The possible explanation for this result is that UFBA is considered the best university in Bahia state. It is located in the capital, the city with the biggest labour market, higher income, and more firms. Therefore, the UFBA diploma acts as a market signal to employers, no matter the student's final GPA. Getting a job can also be related to non-cognitive skills, such as an extrovert personality and communication skills. Unfortunately, the data set does not allow an investigation of these possible mechanisms.

Table 5: Effects on employment and income

Years after graduation	Employment			Income		
	Everyone (1)	STEM (2)	Not STEM (3)	Everyone (4)	STEM (5)	Not STEM (6)
Panel A: Affirmative action students						
One year	–0.0248	0.0248	–0.0172	0152	0.493***	–0.118
	(0.0642)	(0.0794)	(0.102)	(0.117)	(0.210)	(0.187)
Observations	2,776	1,512	1,264	2,134	1,070	1,064
Two years	–0.0611	–0.0831	0.0037	0.139	0.351	–0.325
	(0.0672)	(0.0988)	(0.0904)	(0.143)	(0.217)	(0.226)
Observations	2,335	1,247	1,088	1,887	953	934
Three years	–0.100	0.123	–0.184	–0.0821	–0.0619	–0.496
	(0.0944)	(0.140)	(0.116)	(0.168)	(0.283)	(0.239)
Observations	1,786	921	865	1,510	746	764
Four years	–0.049	0.351***	–0.295***	0.0085	0.482*	–0.578**
	(0.0915)	(0.163)	(0.107)	(0.162)	(0.292)	(0.226)
Observations	1,295	664	631	1,121	553	568
Panel B: Regular students						
One year	–0.0309	–0.0125	–0.0337	–0.0339	0.171	–0.174
	(0.0418)	(0.0545)	(0.0780)	(0.104)	(0.174)	(0.173)
Observations	5,043	2,784	2,259	3,564	1,846	1,718
Two years	0.104*	0.221***	0.0438	0.0112	0.164	–0.141**
	(0.0502)	(0.0772)	(0.0744)	(0.103)	(0.143)	(0.183)
Observations	4,233	2,255	1,978	3,210	1,630	1,580
Three years	–0.009	–0.0206	–0.0009	–0.0166	0.154	–0.250
	(0.0601)	(0.0877)	(0.0813)	(0.131)	(0.196)	(0.211)
Observations	3,255	1,667	1,588	2,584	1,271	1,313
Four years	0.0134	0.0498	–0.0267	0.0672	0.256	–0.243
	(0.0636)	(0.0776)	(0.097)	(0.140)	(0.185)	(0.246)
Observations	2,434	1,281	1,153	2,022	1,035	987

Note: this table presents the estimated sharp RD at the first class cut-off. All models estimated in this table were controlled by gender, course fixed effects, and year of entry fixed effects. RDs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for entrance score is selected based on Calonico et al.'s (2014) procedure. Robust standard errors are in parentheses. ***, **, * represent statistical significant at the 1, 5, and 10 per cent levels, respectively.

Source: authors' calculations based on UFBA and RAIS data.

6 Conclusion

This paper exploits the class allocation rule to study whether the class environment improves or harms academic performance and labour market outcomes. The main results suggest that being the last among the better students is harmful to affirmative action students, but not for regular students. The results are stronger for affirmative action students in STEM majors. We find no clear effects on the labour market.

This finding points out that affirmative action is a necessary policy to give an opportunity to disadvantaged students, but this policy does not guarantee academic success. Most of the affirmative action students enter UFBA with lower background skills. Therefore, policies that help these students to close the gap are also necessary.

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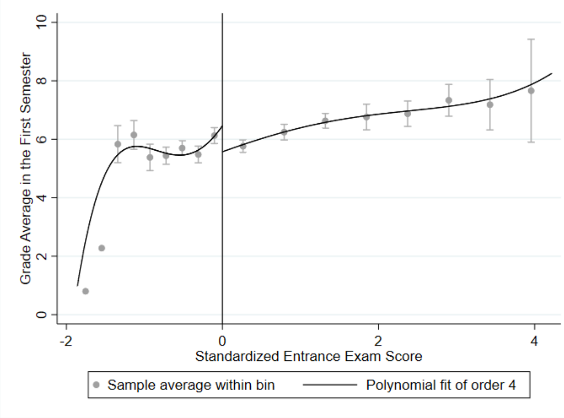
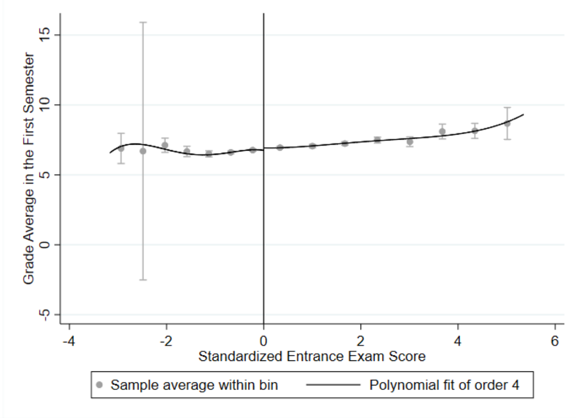
Appendix A: Figures and tables

Figure A1: Affirmative action students' academic achievement along the standardized entrance exam score

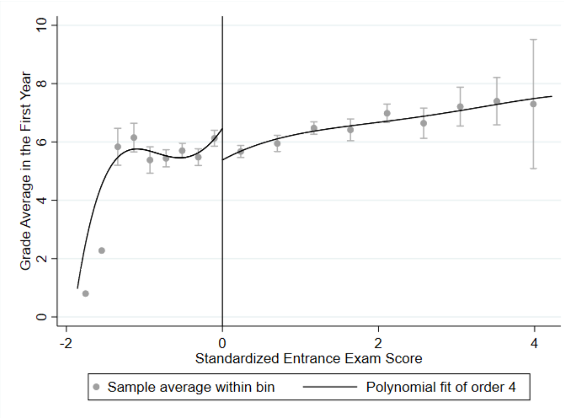
(a) First semester: STEM



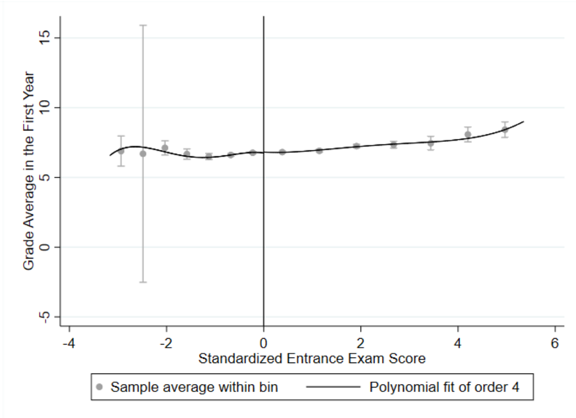
(b) First semester: not STEM



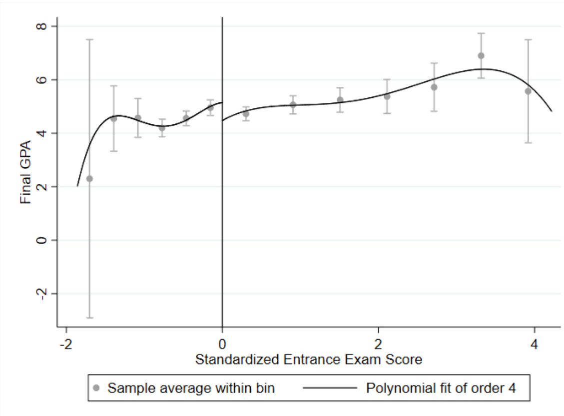
(c) First year: STEM



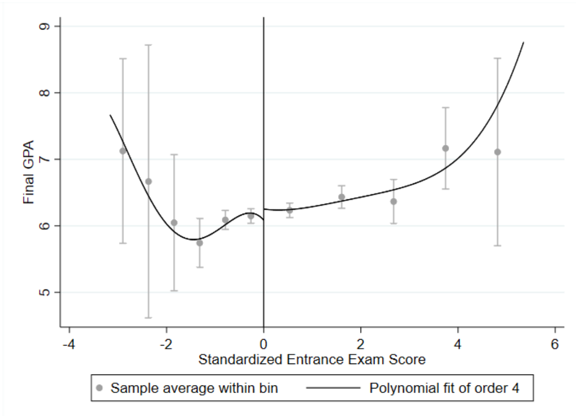
(d) First year: not STEM



(e) CR: STEM



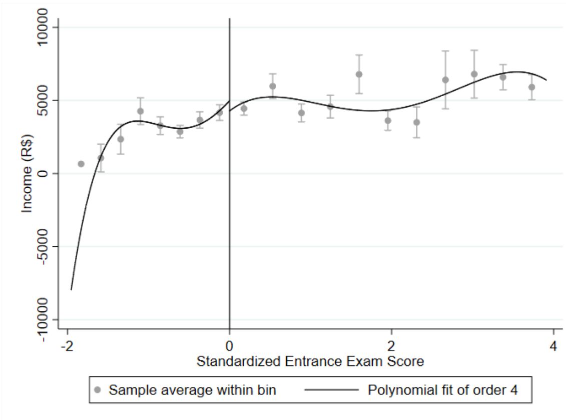
(f) CR: not STEM



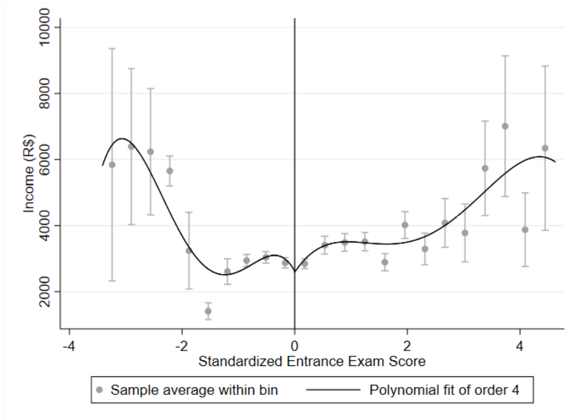
Source: authors' own calculations.

Figure A2: Affirmative action students' performance in the labour market along the standardized entrance exam score

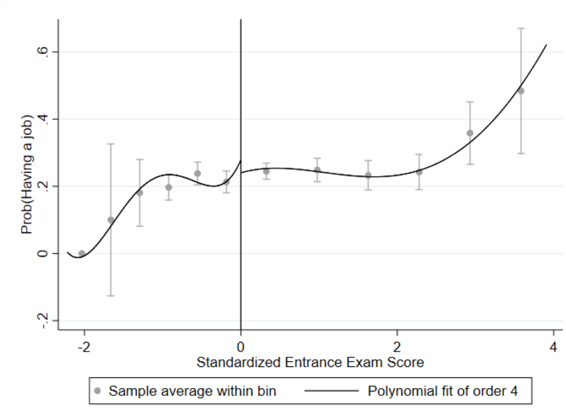
(a) Income: STEM



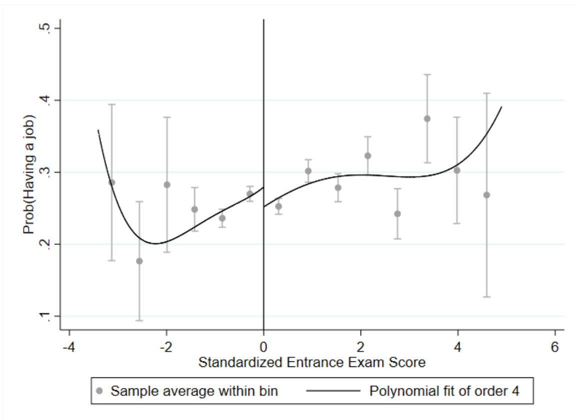
(b) Income: not STEM



(c) Prob(Having a job): STEM



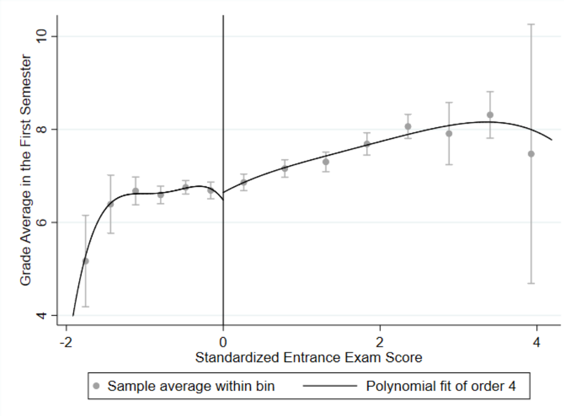
(d) Prob(Having a job): not STEM



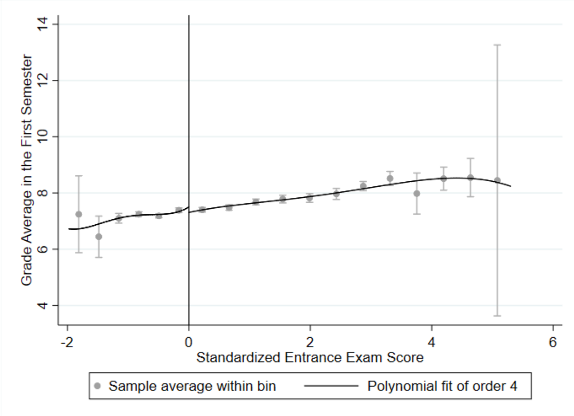
Source: authors' own calculations.

Figure A3: Regular students' academic achievement along the standardized entrance exam score

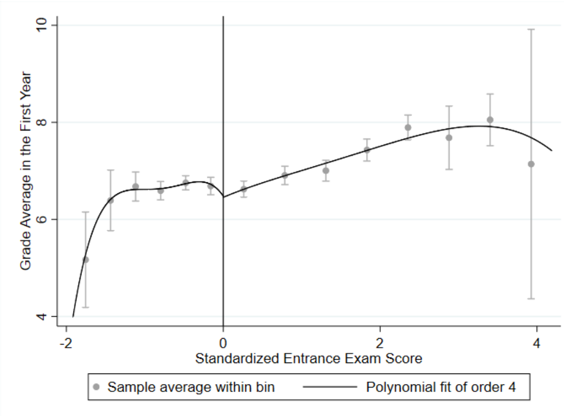
(a) First semester: STEM



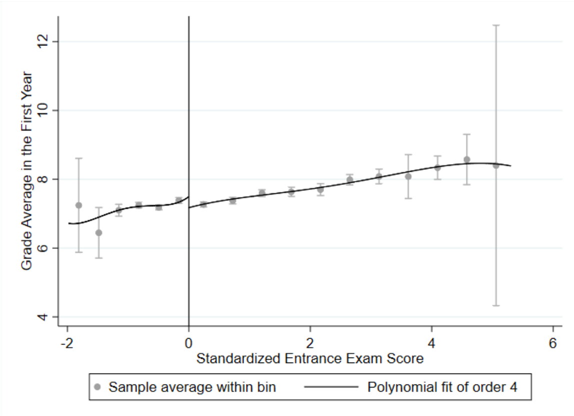
(b) First semester: not STEM



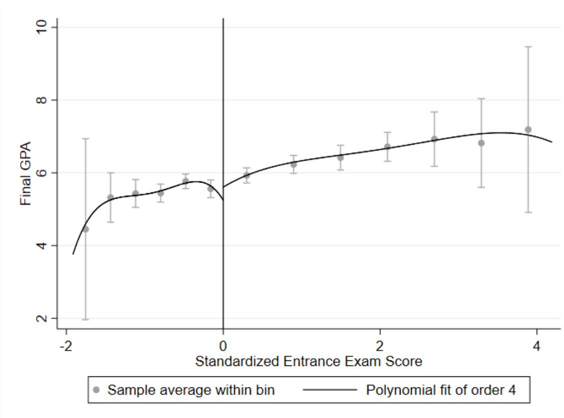
(c) First year: STEM



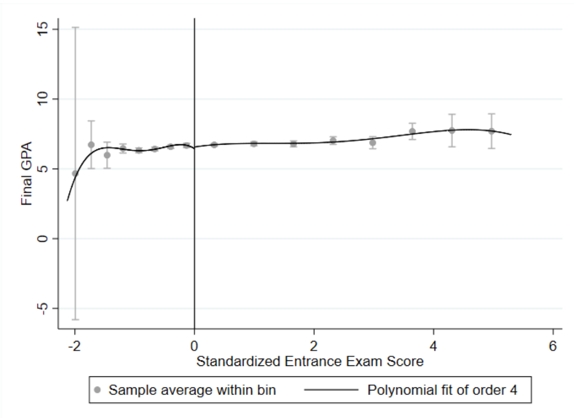
(d) First year: not STEM



(e) CR: STEM



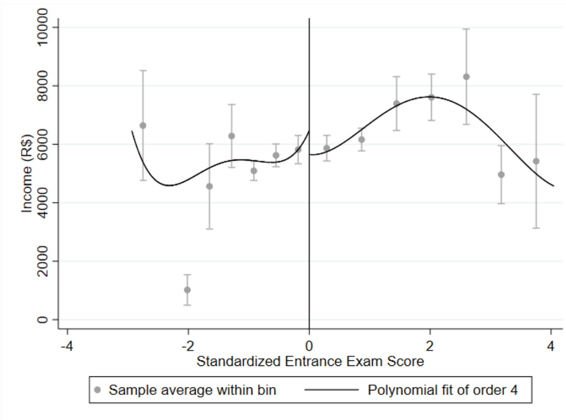
(f) CR: not STEM



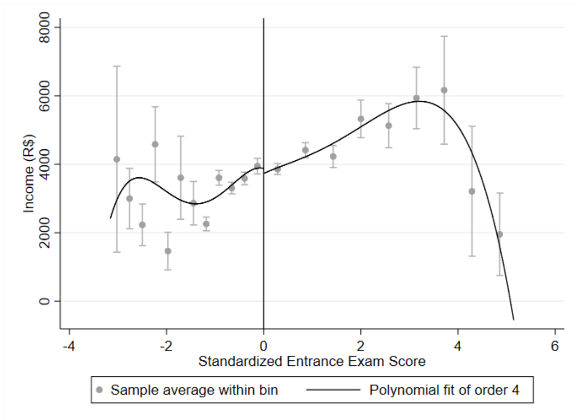
Source: authors' own calculations.

Figure A4: Regular students' performance in the labour market along the standardized entrance exam score

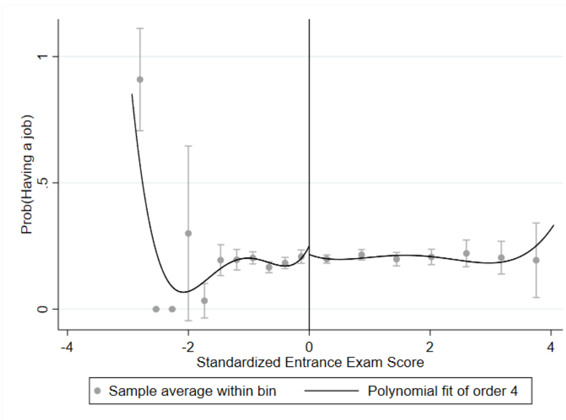
(a) Income: STEM



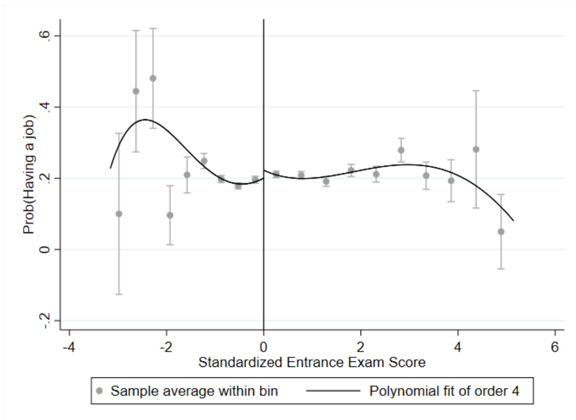
(b) Income: not STEM



(c) Prob(Having a job): STEM



(d) Prob(Having a job): not STEM



Source: authors' own calculations.

Table A1: Manipulation test using local polynomial density estimation

Method	Triangular (default)	Epanechnikov	Asymptotic plugin errors
Quotas & STEM	0.185	0.256	0.183
Quotas & non-STEM	0.055	0.106	0.047
Regular & STEM	0.259	0.318	0.282
Regular & non-STEM	0.941	0.778	0.897

Note: table values are the robust *p*-values of the manipulation test proposed by Cattaneo et al. (2020). Column 1 uses a triangular kernel (program default). Column 2 uses the Epanechnikov kernel. Column 3 uses a triangular kernel with asymptotic plugins errors instead of the default jackknife errors.

Source: authors' calculations based on UFBA and RAIS data.

Table A2: Effects of class allocation for affirmative action students of STEM courses using different bandwidth estimation methods

Dependent variables	mserd	msetwo	msesum	msecomb1	msecomb2	cerrd	certwo	cersum	cercomb1	cercomb2
First semester GPA	–0.784***	–1.031***	–0.767***	–0.767***	–0.770***	–0.765***	–1.043***	–0.825***	–0.825***	–0.823***
	(0.235)	(0.284)	(0.280)	(0.280)	(0.265)	(0.246)	(0.272)	(0.287)	(0.287)	(0.262)
First year GPA	–1.079***	–1.300***	–1.095***	–1.095***	–1.098***	–1.129***	–1.320***	–1.177***	–1.177***	–1.174***
	(0.227)	(0.248)	(0.237)	(0.237)	(0.235)	(0.228)	(0.243)	(0.211)	(0.211)	(0.209)
Final GPA	–0.673	–0.388	–0.679	–0.673	–0.676	–0.642	–0.437	–0.657	–0.642	–0.636
	(0.462)	(0.478)	(0.458)	(0.462)	(0.462)	(0.474)	(0.479)	(0.471)	(0.474)	(0.473)
Dropout	–0.024	–0.045	–0.025	–0.025	–0.027	–0.025	–0.049	–0.030	–0.030	–0.029
	(0.121)	(0.136)	(0.126)	(0.126)	(0.126)	(0.122)	(0.139)	(0.126)	(0.126)	(0.125)
Failures	1.758*	2.332**	1.966*	1.966*	1.916*	2.015**	2.448***	2.210**	2.210**	2.149**
	–1014	(0.917)	–1036	–1036	–1018	–1013	(0.864)	–1041	–1041	–1028
Graduation in time	0.117	0.125	0.117	0.117	0.117	0.122	0.133	0.122	0.122	0.122
	(0.110)	(0.114)	(0.110)	(0.110)	(0.110)	(0.126)	(0.129)	(0.125)	(0.126)	(0.126)
Observations	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250

Note: the following types of optimal band estimation were used: mserd specifies one common mean squared error (MSE)-optimal bandwidth selector for the RD treatment-effect estimator; msetwo specifies two different MSE-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; msesum specifies one common MSE-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); msecomb1 specifies min(mserd, msesum); msecomb2 specifies median(msetwo, mserd, msesum) for each side of the cut-off separately; cerrd specifies one common coverage error-rate (CER)-optimal bandwidth selector for the RD treatment-effect estimator; certwo specifies two different CER-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; cersum specifies one common CER-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); cercomb1 specifies min(cerrd, cersum); cercomb2 specifies median(certwo, cerrd, cersum) for each side of the cut-offs.

Source: authors' calculations based on UFBA and RAIS data.

Table A3: Effects of class allocation for affirmative action students of non-STEM courses using different bandwidth estimation methods

Dependent variables	mserd	msetwo	msesum	msecomb1	msecomb2	cerrd	certwo	cersum	cercomb1	cercomb2
First semester GPA	0.030	0.050	0.014	0.014	0.031	0.020	0.017	–0.005	–0.005	0.012
	(0.133)	(0.134)	(0.146)	(0.146)	(0.137)	(0.141)	(0.135)	(0.153)	(0.153)	(0.146)
First year GPA	–0.120	–0.070	–0.151	–0.151	–0.125	–0.138	–0.102	–0.171	–0.171	–0.153
	(0.109)	(0.106)	(0.127)	(0.127)	(0.116)	(0.118)	(0.108)	(0.130)	(0.130)	(0.125)
Final GPA	0.031	0.046	0.088	0.031	0.044	0.017	–0.006	0.063	0.017	0.011
	(0.202)	(0.198)	(0.175)	(0.202)	(0.196)	(0.209)	(0.205)	(0.182)	(0.209)	(0.203)
Dropout	–0.044	–0.049	–0.047	–0.044	–0.045	–0.044	–0.046	–0.046	–0.044	–0.043
	(0.042)	(0.042)	(0.041)	(0.042)	(0.042)	(0.043)	(0.040)	(0.042)	(0.043)	(0.043)
Failures	1.288*	1.419**	1.338*	1.338*	1.334*	1.466**	1.623**	1.595**	1.595**	1.542**
	(0.677)	(0.670)	(0.699)	(0.699)	(0.688)	(0.704)	(0.696)	(0.735)	(0.735)	(0.720)
Graduation in time	–0.007	–0.006	–0.009	–0.009	–0.008	–0.010	–0.010	–0.013	–0.013	–0.009
	(0.028)	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)	(0.029)	(0.030)	(0.030)	(0.029)
Observations	4,315	4,315	4,315	4,315	4,315	4,315	4,315	4,315	4,315	4,315

Note: the following types of optimal band estimation were used: mserd specifies one common MSE-optimal bandwidth selector for the RD treatment-effect estimator; msetwo specifies two different MSE-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; msesum specifies one common MSE-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); msecomb1 specifies min(mserd, msesum); msecomb2 specifies median(msetwo, mserd, msesum) for each side of the cut-off separately; cerrd specifies one common CER-optimal bandwidth selector for the RD treatment-effect estimator; certwo specifies two different CER-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; cersum specifies one common CER-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); cercomb1 specifies min(cerrd, cersum); cercomb2 specifies median(certwo, cerrd, cersum) for each side of the cut-offs.

Source: authors' calculations based on UFBA and RAIS data.

Table A4: Effects of class allocation for regular students of STEM courses using different bandwidth estimation methods

Dependent variables	mserd	msetwo	msesum	msecomb1	msecomb2	cerrd	certwo	cersum	cercomb1	cercomb2
First semester GPA	–0.109	0.056	–0.063	–0.063	–0.103	–0.082	0.016	–0.041	–0.041	–0.079
	(0.253)	(0.233)	(0.244)	(0.244)	(0.252)	(0.250)	(0.245)	(0.234)	(0.234)	(0.253)
First year GPA	–0.371	–0.239	–0.335	–0.335	–0.375	–0.349	–0.284	–0.313	–0.313	–0.348
	(0.228)	(0.223)	(0.224)	(0.224)	(0.233)	(0.226)	(0.233)	(0.220)	(0.220)	(0.237)
Final GPA	–0.046	–0.002	–0.032	–0.032	–0.053	–0.034	–0.002	–0.022	–0.022	–0.033
	(0.394)	(0.397)	(0.397)	(0.397)	(0.401)	(0.396)	(0.426)	(0.396)	(0.396)	(0.410)
Dropout	–0.058	–0.059	–0.055	–0.055	–0.051	–0.055	–0.069	–0.053	–0.053	–0.051
	(0.069)	(0.077)	(0.073)	(0.073)	(0.072)	(0.073)	(0.082)	(0.077)	(0.077)	(0.076)
Failures	1.438**	1.535**	1.412**	1.445**	1.438**	1.568**	1.600***	1.551**	1.573**	1.572**
	(0.658)	(0.620)	(0.669)	(0.666)	(0.662)	(0.644)	(0.538)	(0.656)	(0.650)	(0.643)
Graduation in time	0.108***	0.098***	0.106***	0.108***	0.105***	0.110***	0.097***	0.109***	0.110***	0.108***
	(0.033)	(0.031)	(0.032)	(0.033)	(0.032)	(0.033)	(0.030)	(0.033)	(0.033)	(0.032)
Observations	2,124	2,124	2,124	2,124	2,124	2,124	2,124	2,124	2,124	2,124

Note: the following types of optimal band estimation were used: mserd specifies one common MSE-optimal bandwidth selector for the RD treatment-effect estimator; msetwo specifies two different MSE-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; msesum specifies one common MSE-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); msecomb1 specifies min(mserd, msesum); msecomb2 specifies median(msetwo, mserd, msesum) for each side of the cut-off separately; cerrd specifies one common CER-optimal bandwidth selector for the RD treatment-effect estimator; certwo specifies two different CER-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; cersum specifies one common CER-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); cercomb1 specifies min(cerrd, cersum); cercomb2 specifies median(certwo, cerrd, cersum) for each side of the cut-offs.

Source: authors' calculations based on UFBA and RAIS data.

Table A5: Effects of class allocation for regular students of non-STEM courses using different bandwidth estimation methods

Dependent variables	mserd	msetwo	msesum	msecomb1	msecomb2	cerrd	certwo	cersum	cercomb1	cercomb2
First semester GPA	0.382**	0.255	0.288*	0.382**	0.334*	0.410**	0.249	0.342**	0.410**	0.368**
	(0.174)	(0.164)	(0.164)	(0.174)	(0.176)	(0.180)	(0.174)	(0.170)	(0.180)	(0.184)
First year GPA	0.147	0.121	0.135	0.147	0.139	0.189	0.114	0.174	0.189	0.180
	(0.164)	(0.157)	(0.161)	(0.164)	(0.164)	(0.168)	(0.167)	(0.166)	(0.168)	(0.168)
Final GPA	0.472**	0.435**	0.450**	0.472**	0.474**	0.489**	0.429*	0.474**	0.489**	0.484**
	(0.211)	(0.215)	(0.196)	(0.211)	(0.208)	(0.227)	(0.224)	(0.216)	(0.227)	(0.226)
Dropout	–0.068*	–0.060	–0.071*	–0.068*	–0.068*	–0.062	–0.059	–0.064	–0.062	–0.063
	(0.041)	(0.038)	(0.040)	(0.041)	(0.041)	(0.042)	(0.041)	(0.041)	(0.042)	(0.042)
Failures	0.045	0.245	0.043	0.045	0.023	0.165	0.305	0.106	0.165	0.150
	(0.475)	(0.397)	(0.456)	(0.475)	(0.471)	(0.520)	(0.444)	(0.492)	(0.520)	(0.516)
Graduation in time	0.013	0.021	0.013	0.013	0.013	0.021	0.034*	0.021	0.021	0.021
	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)
Observations	6,791	6,791	6,791	6,791	6,791	6,791	6,791	6,791	6,791	6,791

Note: the following types of optimal band estimation were used: mserd specifies one common MSE-optimal bandwidth selector for the RD treatment-effect estimator; msetwo specifies two different MSE-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; msesum specifies one common MSE-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); msecomb1 specifies min(mserd, msesum); msecomb2 specifies median(msetwo, mserd, msesum) for each side of the cut-off separately; cerrd specifies one common CER-optimal bandwidth selector for the RD treatment-effect estimator; certwo specifies two different CER-optimal bandwidth selectors (below and above the cut-off) for the RD treatment-effect estimator; cersum specifies one common CER-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); cercomb1 specifies min(cerrd, cersum); cercomb2 specifies median(certwo, cerrd, cersum) for each side of the cut-offs.

Source: authors' calculations based on UFBA and RAIS data.

Table A6: Effects of class allocation (conventional estimation)

Dependent variables	Affirmative action students			Regular students		
	Everyone (1)	STEM (2)	Not STEM (3)	Everyone (4)	STEM (5)	Not STEM (6)
First semester GPA	–0.168	–0.713***	0.038	0.228*	–0.144	0.313**
	(0.131)	(0.218)	(0.114)	(0.122)	(0.239)	(0.157)
First year GPA	–0.384***	–1.021***	–0.111	0.004	–0.397*	0.085
	(0.122)	(0.215)	(0.095)	(0.114)	(0.218)	(0.145)
Final GPA	–0.114	–0.652*	0.040	0.338**	–0.099	0.406**
	(0.151)	(0.384)	(0.165)	(0.162)	(0.356)	(0.189)
Dropout	–0.030	–0.018	–0.045	–0.066**	–0.058	–0.064*
	(0.031)	(0.103)	(0.035)	(0.026)	(0.060)	(0.034)
Failures	1.442***	1.713*	1.176**	0.578*	1.310**	0.160
	(0.495)	(0.880)	(0.576)	(0.306)	(0.581)	(0.415)
Graduation in time	0.003	0.105	–0.006	0.033*	0.099***	0.013
	(0.025)	(0.099)	(0.025)	(0.017)	(0.031)	(0.016)
Observations	5,565	1,250	4,315	8,915	2,124	6,791

Note: this table presents the estimated sharp RD at the first class cut-off. All models estimated in this table were controlled by gender, course fixed effects, and year of entry fixed effects. RDs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for entrance score is selected based on Calonico et al.'s (2014) procedure. Standard errors are in parentheses. ***, **, * represent statistical significant at the 1, 5, and 10 per cent levels, respectively.

Source: authors' calculations based on UFBA and RAIS data.

Table A7: Effects of class allocation (bias-corrected estimation)

Dependent variables	Affirmative action students			Regular students		
	Everyone (1)	STEM (2)	Not STEM (3)	Everyone (4)	STEM (5)	Not STEM (6)
First semester GPA	–0.199	–0.784***	0.030	0.280**	–0.109	0.382**
	(0.131)	(0.218)	(0.114)	(0.122)	(0.239)	(0.157)
First year GPA	–0.416***	–1.079***	–0.120	0.049	–0.371*	0.147
	(0.122)	(0.215)	(0.095)	(0.114)	(0.218)	(0.145)
Final GPA	–0.123	–0.673*	0.031	0.390**	–0.046	0.472**
	(0.151)	(0.384)	(0.165)	(0.162)	(0.356)	(0.189)
Dropout	–0.032	–0.024	–0.044	–0.071***	–0.058	–0.068**
	(0.031)	(0.103)	(0.035)	(0.026)	(0.060)	(0.034)
Failures	1.543***	1.758**	1.288**	0.493	1.438**	0.045
	(0.495)	(0.880)	(0.576)	(0.306)	(0.581)	(0.415)
Graduation in time	0.005	0.117	–0.007	0.038**	0.108***	0.013
	(0.025)	(0.099)	(0.025)	(0.017)	(0.031)	(0.016)
Observations	5,565	1,250	4,315	8,915	2,124	6,791

Note: this table presents the estimated sharp RD at the first class cut-off. All models estimated in this table were controlled by gender, course fixed effects, and year of entry fixed effects. RDs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for entrance score is selected based on Calonico et al.'s (2014) procedure. Standard errors are in parentheses. ***, **, * represent statistical significant at the 1, 5, and 10 per cent levels, respectively.

Source: authors' calculations based on UFBA and RAIS data.