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The effect of class assignment on academic performance and the labour market

Evidence from a public federal university in Brazil

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Abstract: Can students' rank in the ability distribution of their class impact their academic achievement? We aim to answer this question using a discontinuity generated by a rule for the distribution of students between classes at a prestigious Brazilian university. The rule means that in almost 30 per cent of its courses, the Federal University of Bahia allocates 50 per cent of the best students in the university entrance exam to the group that starts in the first semester, and the other 50 per cent to the group that starts in the second semester. We also explore the fact that the Federal University of Bahia was the first federal university in Brazil to adopt affirmative action for low-income individuals. In general, the results indicate that coming last among the best students of the first class negatively impacts student performance, and this effect is greater when considering students from affirmative action programmes and for courses in the field of technology. But the results in the labour market are not unique. Being in the first class could have positive or negative effects in terms of the labour market, depending on whether the students are part of the affirmative action quota or not.

Keywords: affirmative action, Brazil, education, labour markets, peer effects

JEL classification: I0, J0, C4

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1 Introduction

Brazil is one of the most unequal countries in the world, and the great majority of studies suggest that the explanations for this phenomenon are in the dynamics of labour income, and more particularly in how education affects the labour market (Fernández and Messina 2018; Ferreira et al. 2017). The unequal access to universities in Brazil is a persistent problem and has impacts on the labour market. Using data from the 2014 annual household survey, Pesquisa Nacional Por Amostra de Domicílios (PNAD), we can see that only 15 per cent of the Brazilian workers with positive income have a university degree and, considering only Afro descendants (blacks and mullatos), who represent 57 per cent of the population of Brazil, the number is even lower: only 10 per cent of Afro-descendent workers have a university degree.[1] When we look only at Bahia state, these numbers are respectively 11 per cent, 83 per cent, and 9 per cent. Bahia is the state of Brazil with the biggest Afro-descendent population.

With the objective of reducing income disparities between individuals, the Brazilian government created policies to expand higher education to poorer localities, and improve access for the neediest population through affirmative action (AA) policies. One of the important AA measures was the Quotas policy, adopted by the Brazilian federal government in 2012.[2]. This is the policy of reserving some of the available places at the most prestigious public universities for students from low-income households.

Some universities had already decided to create their own policy before the intervention of the federal government. Among others, the Federal University of Bahia (UFBA) was the first federal university to adopt AA quotas (Quotas, hereafter) in 2004, focusing on low-income former students from public high schools. With Quotas, the demographic of UFBA changed, allowing the entry of poorer individuals who did not have the opportunity to access the best secondary schools. Little is known about the effects of the interaction between Quota and non-Quota students in terms of academic performance and the labour market, but the effect of peers in various social relations has been widely analysed and documented in the economic literature. It is important to know whether each student's performance, motivation, and effort are impacted by their interactions with other students and what is the magnitude (Sacerdote 2011).

Despite the importance of understanding peer effects, the endogenous nature of this issue makes them difficult to compute. People tend to cluster in work environments, at school, in communities, etc., based on their observable characteristics. There is, therefore, an issue related to the self-selection of individuals into certain groups. In this sense, many studies have tried to overcome the problem of endogeneity using randomized controlled trials (Carrell et al. 2013; Duflo et al. 2011). Some authors have examined the question by looking at university roommates (Brunello et al. 2010; Eisenberg et al. 2013; Kremer and Levy 2003; Zimmerman 2003), while Bursztyn and Jensen (2015) and Bursztyn et al. (2019) have demonstrated that the peer effects may generate peer pressure effects on students, reducing their efforts.

Our identification strategy is based on a rule of entry at UFBA that assign students to different classes. In almost 30 per cent of UFBA courses, selected students were allocated across two periods, with 50 per cent of the best-ranked students at the university entrance exam allocated to the first semester (which

[1] The year 2004 was the last year before the beginning of the economic crisis. The PNAD (the Brazilian National Household Sample Survey) is an annual household survey with a sample size equal to approximately 300,000 households, or 1/500 of the Brazilian population. It was designed to produce a picture of the socio-economic conditions of the Brazilian population. It covers all urban and almost all rural areas, except the Amazon region. This survey has been conducted on a regular basis since 1981 by the IBGE (the Brazilian Census Bureau), except in 1991 and 2000—when census data were collected—and in 1994—when there was a budgetary crisis. The PNAD also contains extensive data on individuals and households.

[2] See www.planalto.gov.br/ccivil_03/_ato2011-2014/2012/lei/l12711.htm

begins in March) until all the positions are filled. Those students cannot choose to begin in the second semester, which begins in August. The remainder of the students are added to a class that only begins in the second semester, respecting the order of the entrance exam ranking and the number of available vacancies for each course. For example, if the economics course has 200 vacancies, there will be two classes with 100 students each, with one beginning in March and the other in August. These classes are created using the Quotas scheme, which means that 45 per cent of the students in each class need to be Quota students.

Beside the discussion of peer effects and AA, this paper also contributes to the tracking literature in education. Tracking is the strategy of clustering similar students together in the same environment. Duflo et al. (2011) showed a positive effect of this policy on Kenya's elementary schools, and Card and Guliano (2016) showed that tracking improved the performance of black and Hispanic students in the USA. But there is no clear consensus in the literature on whether tracking leads to significant achievement gains, and there is little evidence of the impacts of tracking at the university level.

The UFBA's rule implies that students will be allocated to different classes, with different average abilities and different classmates. The students in each semester will have different peers who can improve or reduce their performance. The question we aim to answer is: 'Can students' rank in the ability distribution of their class impact their academic achievement and labour market outcomes?' To answer this question, we use the grade of the last student of each group allocated in the first class as a cut-off point in a sharp regression discontinuity design scheme. The main assumption is that students who complete the university entrance exam are unable to know the grade needed to be in the first class, since this depends on the performance of the other students.

In Figure 1 we show that when we look at students who have grades close to cutoff between classes, we are comparing: (1) Quota students who are in the last rank of the class skill distribution in the first semester with the best Quota students who are in the middle of the class skill distribution in the second semester; and (2) the last non-Quota students of the first semester who are located in the middle of the class skill distribution in the first semester with non-Quota students who are at the top of the class skill distribution in the second semester. We can also see that, as a result of the entrance selection format through the entrance exam, the first class always has an average score (better peers) superior to the second class. So, the intersection of AA and the rule of allocating students between semesters using their vestibular score produce a kind of tracking policy at the university. In Figure 1 we show only data for one major in a specific year, but this pattern occurs in all majors and years.

In this paper, we add to the literature by analysing how peer effects can play a relevant role in students' performance at one flagship university in a low- to middle-income country. Although other working papers have done similar analyses (Andre and Carvalho 2016; Ribas et al. 2018), our paper is the first to explore the heterogeneity of the peer effect when considering non-Quota and Quota students. That the effects of the relationship between students from different social groups impact learning and development of abilities is a growing concern among researchers in the field (Rao 2019), but little is known about those effects at the university level. The problem is that placing students in classes with generally stronger classmates could generate a mismatch for the intended beneficiaries of AA (Rothstein and Yoon 2008).

In general, the results of academic performance indicate that being among the last of the first class is worse than being among the first in the second class. This suggests that higher-achieving peers could have a negative impact on the learning of lower-ability students; in other words, they can act as a peer pressure mechanism. When the analysis was performed by knowledge field, the effect is even stronger when analysing technology courses. A potential criticism to these results could be that teachers know that the classes have different mean abilities and reduce the difficulty of exams for the classes that begin in August. To overcome this problem, we also perform an analysis comparing the performance at different lectures, because this allows us to control for teachers fixed effects. The results show that teachers' behaviours do not affect the results, indicating that the most plausible explanation for the results found is peer effects.

In addition, the results for the labour market suggest different patterns between Quota and non-Quota students, with being among the last of the first class being worse than being among the first in the second class for non-Quota students, but the opposite for Quota students. This suggests that, despite the negative effects on academic performance, Quota students in the first class can benefit from the interaction with higher-achieving peers when it comes to the labour market.

2 Previous literature

There is an extensive literature dealing with peer effects, with a predominance of analyses in education economics. Manski (1993) states that peer effects can occur in three ways: (1) endogenous effects, which occur when the behaviour of the individual changes due to a variation in the behaviour of their peers; (2) exogenous effects, which occur when the behaviour of the individual varies due to the pretreatment characteristics of their peers; and (3) correlated effects, which relate to a treatment common to the individual and his/her peers.

Carrell et al. (2009) cite examples of how these three types of peer effects can occur in higher education. The endogenous effect could be the increase of the average performance of the class in the subjects studied. The exogenous effect may appear with a variation in socio-economic characteristics or the average ability of classmates. The correlated effect could be, for example, interactions with certain teachers. It is important to emphasize that, depending on the environment in which they are inserted, interactions with colleagues can also cause adverse effects on student behaviour. That is, the peer effect could generate peer pressure effects on individuals, as pointed out by Bursztyn and Jensen (2015) and Bursztyn et al. (2019).

The literature points out that students benefit from peers with higher performance (Eisenkopf 2009; Sund, 2008). They also can show improvement when placed alongside peers with similar ability levels (Duflo et al. 2011). There is also literature that finds positive effects of girls' presence in the classroom on student performance (Eisenkopf et al. 2014; Hoxby 2000;Hu 2015; Oosterbeek and Van Ewijk 2013). Much of the literature focuses on peer effects between roommates at universities. Zimmerman (2003) found positive effects of roommates on grammar and reading scores on the SAT test, but found very small effects on maths scores. Eisenberg et al. (2013) found a peer effect of over-consumption of alcohol, and Kremer and Levy (2003) show a negative effect on males' scores when sharing a room with alcohol-consuming peers before entering university. Brunello et al. (2010) find that positive effects of peers among roommates depend on the student's field of study, with engineering, maths, and natural sciences courses seeing positive effects. Carrell et al. (2009) obtained evidence for the same in the humanities and social sciences.

Carrell et al. (2013) randomized freshmen of the first year in the United States Air Force Academy (USAFA) into two groups and found a negative effect on the scores of individuals of lesser ability who were arbitrarily allocated to the same room as individuals of greater ability. For individuals with average ability, there was a positive effect on their grades; for the most skilled individuals there was no change in their performance. The authors' hypothesis is that, even if individuals with different skill levels are to study in the same room, there is a tendency for individuals to interact in more homogeneous subgroups, which interferes with the effect of this type of policy.

The main hypothesis used for this result is homophily—that is, the tendency of individuals to relate to other individuals with similar characteristics. Increasing the average ability in a particular class may cause students of lower ability to isolate themselves in a subgroup, causing their grades to converge to a lower value.

There is a literature that focuses on the effects of AA on college performance and the labour market. Most of the literature focuses on US AA effects on college performance (Alon and Tienda 2005; Arcidiacono and Lovenheim 2016; Arcidiacono et al. 2016; Fischer and Massey 2007; Massey and Mooney 2007) and labour market outcomes (Andrews et al. 2016; Arcidiacono 2005; Black and Smith 2004, 2006; Dale and Krueger 2014; Hoekstra 2009; Loury and Garman 1993, 1995; Wydick 2002).

Hoekstra (2009), for example, shows that attending a US flagship state university increases the earnings of white men who applied in the late 1980s by about 20 per cent. He finds that attending a selective state university also increases earnings by about 20 per cent.

Dale and Krueger (2014) show the difference of attending a selective college by race, linking the college characteristics of persons who entered college in 1976 and 1989 with their earnings in 2007. They show that returns are large for blacks, Hispanics, and those whose parents have relatively low education.

There are some papers that explore these issues in other countries (Alon and Malamud 2014; Bagde et al. 2016; Frisancho and Krishna 2016). There are few papers that explore these questions in Brazil, and fewer that use administrative datasets. Francis-Tan and Tannuri-Pianto (2012, 2013) examine the racial Quotas policy at the University of Brasilia. They find evidence that these racial Quotas increased the proportion of black students, and that displaced applicants were, by many measures, from families with lower socio-economic status. Francis-Tan and Tannuri-Pianto (2018) estimate the impact of attending a flagship university in the capital of Brazil. They explore the fact that the University of Brasilia (UnB) reserved 20 per cent of admissions slots for persons who self-identified as black in 2004–05. They found that attending a flagship university has a large impact on AA students, but they did not find any effect on non-AA students.

3 Methodology

3.1 UFBA's entrance exam (vestibular) and quotas policy

The history of UFBA began on 18 October 1808, with the UFBA Medical School, the first university in Brazil, instituted by Prince Regent Dom João VI. Today, UFBA is one of the largest institutions of higher education in Brazil, both in terms of structure and number of students. It is the second biggest university in the Northeast region. In 2017, UFBA had 105 undergraduate courses, 93 of which were in the capital Salvador, 136 *stricto sensu* postgraduate courses, of which 82 were masters and 54 were PhDs, in addition to 42 postgraduate courses *lato sensu*. In that same year, the UFBA budget was R$1,620,709,982.00 (US$413,446,423.98) (UFBA 2018), and it offered 8,875 vacancies to new students that did the Vestibular (the entrance exam) in 2016. In that year, almost 200,000 people did the Vestibular (UFBA 2016). An important feature is that, as with all public universities in Brazil, UFBA is entirely tuition-free; making it the best, and sometimes only, option for students from poorer families to access college.

The Vestibular was the only way students could enter UFBA until 2013. It had two phases. The first was an objective exam with questions about Portuguese grammar and reading, maths, physics, chemistry, geography, biology, foreign language (English or Spanish), history, and philosophy. Some students were selected to the second phase, with discursive question in the field of the chosen course. For example, students who chose engineering needed to answer questions about maths, physics, and chemistry. After the exams, all students were ranked, and they were selected depending on the number of available places in each course. After 2013, the Vestibular was replaced by a national selection process called

SISU (Sistema de Selecao Unificada). Since SISU was adopted, UFBA stopped collecting information about students' grades and socio-economic characteristics, so we work here only with students who did the Vestibular up to 2013.

An important issue that makes our contribution original is that since 2004 UFBA has adopted a policy of reserving vacancies for former students from public high schools. The idea of the policy was to offer the opportunity to enter the state flagship university to students who had access to lower-quality basic education, most of whom are poor.[3] UFBA established different criteria so that students could fit this form of entry, and for each criterion there is a different proportion of places reserved for each class. Of the total vacancies, 36.55 per cent are intended for public school students who declare themselves to be Afro-descendent, 6.45 per cent are for public school students of any ethnic group, and 2 per cent are reserved for indigenous students. Overall, 45 per cent of the total vacancies offered each year are filled by Quota applicants (CONSEPE 2004).

Until 2013, almost 30 per cent of UFBA's courses selected students to study in two periods. The best 50 per cent of students (those who scored highest on the Vestibular) were select to start at the university in March; the other 50 per cent start in August. Students could not choose which semester they wanted to start, they are allocated only with respect to the Vestibular ranking for each course. If a student was selected to the first semester and chose not to start at UFBA in that semester, he or she would need to do the Vestibular again the following year. The classes are created in accordance with the ranking of each group of students, so 45 per cent of the class at each semester will be filled by Quota applicants. This rule created a discontinuity in the allocation process, with the last student of the first class in each group being the cut-off point that separates the two groups of students.

Students who enter university through the Quotas policy need to fulfil the same entrance exam as all the other students. However, the selection process is carried out independently for each category of students, obeying the descending order of the overall score calculated from the students' performance in the two phases of the Vestibular (CONSEPE 2004). In this case, if the course has 100 available places for the first semester and 100 for the second semester, 45 of these places will be filled by Quotas applicants.

This policy of UFBA is of importance since the university is in the state of Bahia, where, according to PNAD data, 83 per cent of the population is Afro-descendent, the highest percentage among all Brazilian states. Data from the PNAD can further illustrate the potential importance of the policy, because people who live in Salvador and Bahia have an average income below the national mean. When we compare these places to São Paulo, the richest city of the country, a person in Salvador receives an average income that is 37 per cent less, and a person in Bahia almost 50 per cent less. We also verify that in Salvador the average income of a white worker is much higher than the average income of a black worker; the difference in 2015 was 45 per cent.

3.2 Data

The data used are not public and were provided by the Information Technology Sector (STI) of UFBA. The administrative records are separated into two bases, one that composes the socio-economic questionnaire held on Vestibular day and contains the grades of all the students taking the test, even those who were not approved, and another that contains the scholastic histories of the students who joined UFBA. We use data from between 2005 and 2013, because after that the entrance exam change to SISU, as explained previously.

The analysis focuses only on courses that have two intakes in the year—that is, courses in which the top 50 per cent of students start the course in the first semester (this semester is March to July) and the

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

other 50 per cent begin the course in the second semester (this semester is August to December). It should be emphasized that the students' allocation among the classes exclusively follows the ranking of the Vestibular grades—that is, students are not entitled to choose to enter university in the first or second semester, allocation is exclusively according to the Vestibular. Using this data we create two samples. The complete sample has a total of 14,886 students, comprising 5,824 Quota and 9,062 non-Quota students who, after the Vestibular, completed registration to start studying at the university. The second sample contains only the students who graduated until 2017, overall 9,519 students, comprising 3,498 Quota and 6,021 non-Quota students.

To access the impact on the labour market we use the Registro Anual de Informações Sociais (RAIS), a database that contain all Brazilian workers with formal contracts. Because RAIS uses the Brazilian social security number we were able to merge these data with UFBA's and identify the students in the labour market. With RAIS we focus on the probability of being employed and wages.

3.3 Empirical strategy and initial evidence

We use a sharp discontinuity regression in which the cut-off is provided by the score of the last student i of group g who entered the first-semester class in each year t and course c. The running variable is calculated as $r_{igtc} = \frac{(S_{igtc} - C_{tgc})}{SD_{tgc}}$, where S_{iyc} 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 course c and year t (cut-off), and SD is the standard deviation of the score for group g in course c and year t. Outcomes Y_{ik} are regressed on the above cut-off indicator $A_i = 1\{r_{igtc \geq 0}\}$, the normalized entrance exam score S_{itc}, age, gender, and on year and course fixed effects, because strikes may have occurred in certain years, affecting the students' performance, and there are certain course particularities that may affect the results. Throughout the analysis, we follow the checklist proposed by Lee and Lemieux (2010). The estimated equation with all covariates has the following specification:

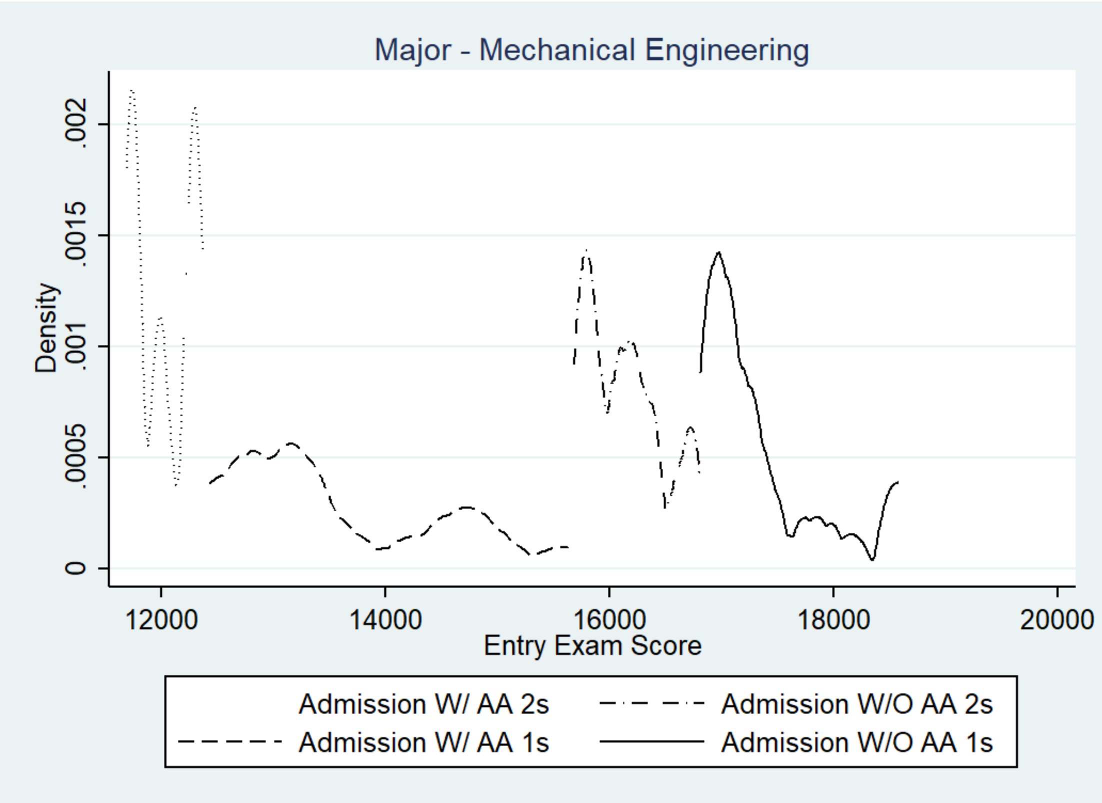
$$Y_{ik} = \beta_0 + \beta_1 r_{igtc} + \beta_2 A_i + \beta_3 r_{igtc} * A_i + \beta_4 S_{ik} + \beta_5 age + \beta_6 gender_i + \gamma_j + \rho_t + \varepsilon_i \qquad (1)$$

We construct tree outcome variables Y_{ik} to measure academic performance as follows. (1) For the average grade in the first semester we divide the sum of the grades in each course by the number of courses taken in the first semester at the university. This variable could be interpreted as the GPA (grade point average) of the first semester. (2) The average grade in the first year, that is the sum of the grades in the first two semesters, for each course divided by the number of courses taken in the first year at the university could be interpreted as the GPA of the first year. (3) The coefficient of performance (GPA) that is measured by the university at the end of the course: this measure is the average grade divided by the number of hours in all courses. With these three variables we intend to measure student performance on a scale of 0 to 10 at different moments over the course. This will make it possible to compare the students as a first-year students and as bachelor's candidates. It is reasonable to think that after the beginning of the course, when students are arbitrarily allocated into two different classes, because in the other years it is possible (or likely) that students will interact with students who have entered the course in other years, we no longer have as much control over the type of peers and the student's position in the ability distribution of their class. γ_j and ρ_t are respectively course and year fixed effects.

In addition to estimating the effect on students' performance, we also estimated the effect of the treatment on the probability of student dropout from the course. For this, the outcome will be equal to 1 if the student does dropout from the course and 0 if the student reaches the end of the course and obtains the diploma.

As we can see in Figure 1, the discontinuity generated by the UFBA class allocation format allows us to compare the outcomes of Quota students at the bottom of their class ability distribution with Quota students who are in the middle of their class ability distribution. For the non-Quota student group we compared top students with students from the middle of the class ability distribution. One limitation of this paper is therefore that it is not possible to compare other positions within the ability distribution of the class. It would be interesting, for example, to compare top students with bottom students, but as we said this is not possible through the regression discontinuity design (RDD) methodology. However, this is the first paper to analyse Quota students and their peer interactions in different positions in the class ability distribution.

Figure 1: Distribution of students by entrance exam grade



Notes: Non-Quota and first-semester students are represented by the solid line. Non-Quota and second-semester students are represented by the dash–dot line. Quota and first-semester students are represented by the dashed line. Quota and second-semester students are represented by the dotted line. The graph represents data about the grades at the Vestibular for students in major mechanical engineering for the 2010 intake.

Source: authors' compilation based on data from the STI.

A potential source of bias in our estimates is teacher behaviour. Teachers know that students who enter in the first semester have Vestibular scores that are higher than students who enter in the second semester. Later, in Table 10, we perform a mean difference test, controlling for the characteristics of individuals to see if there is any evidence that teachers grade on a curve. We can define grading on a curve as not keeping the learning level constant when better peers have a negative impact on a student's grade (Calsamiglia and Loviglio 2019): if teachers grade on a curve, we would expect a negative average difference, since controlling for difference in ability and socio-economic characteristics, students in the first class (with more skilled peers) would have a negative impact on their grades as a result of this possible teacher interference. Our results indicate no evidence that teachers grade on a curve for technology and social science courses, which are the main focus of this paper. We also created a sample using the grades of students in each class of the first semester, which allows us to incorporate a teacher fixed effect (τ_j) in Equation 1:

$$Y_{ik} = \beta_0 + \beta_1 r_{igtc} + \beta_2 A_i + \beta_3 r_{igtc} * A_i + \beta_4 S_{ik} + \beta_5 age + \beta_6 gender_i + \gamma_j + \rho_t + \tau_j + \varepsilon_i \tag{2}$$

Finally, to access the labour market outcomes we estimate the following specification, where Y_{ik} is the income logarithm or the likelihood of being employed in the formal labour market.

$$Y_{ik} = \beta_0 + \beta_1 r_{igtc} + \beta_2 A_i + \beta_3 r_{igtc} * A_i + \beta_4 S_{ik} + \beta_5 age + \beta_6 gender_i + \beta_7 score + \beta_8 GPA + \gamma_j + \rho_t + \varepsilon_i \quad (3)$$

Tables 1 and 2 show the descriptions of the dependent variables and the explanatory variables that were used in the estimation. In both tables, panel B presents the descriptive statistics around the cut-off. The variable that defines the discontinuity in the probability of student allocation is the grade at the Vestibular. More specifically, there will be for each course and year a different cut-off grade between the first-semester and second-semester classes.

Table 1: Descriptive statistics: Quota students

	First class	Second class	Mean difference	*p*-values
Panel A: All Quota students				
Vestibular grade	13,185 (1,483)	12,255 (1,221)	930	0
Age	21.37 (5.6)	21.6 (5.6)	0.23	0.114
Gender	0.473 (0.498)	0.452 (0.499)	0.021	0.105
First-semester grades	6.97 (1.5)	6.57 (1.5)	0.4	0
GPA	6.06 (2.25)	5.85 (2.12)	0.21	0
Panel B: Quota students around the cut-off ($h = 0.3$)				
Vestibular grade	12,397 (1,153)	12,351 (1,190)	46	0.417
Age	21.56 (5.85)	21.59 (5.63)	0.03	0.915
Gender	0.434 (0.495)	0.468 (0. 499)	0.034	0.155
First-semester grades	6.6 (1.49)	6.68 (1.44)	0.08	0.327
GPA	5.82 (2.14)	5.93 (2.1)	0.11	0.247

Notes: *Vestibular* is the average grade of students in the Vestibular, in which the maximum grade is 20,000. *Gender* is the percentage of men in the class. *Grades* is the average grade of students in university courses. *GPA* is calculated at the end of the course and corresponds to the grade of the courses weighted by the workload of each course.

Source: authors' compilation based on data from the STI.

Table 2: Descriptive statistics: non-Quota students

	First class	Second class	Mean difference	*p*-values
Panel A: all non-Quota students				
Vestibular grade	15,151 (1,946)	14,274 (1,906)	877	0
Age	19.39 (3.71)	19.5 (3.78)	0.11	0.114
Gender	0.44 (0.496)	0.45 (0.497)	0.01	0.389
First-semester grades	7.49 (1.42)	7.28 (1.32)	0.21	0
GPA	6.58 (2.25)	6.5 (2.08)	0.08	0.097
Panel B: non-Quota students around the cut-off (h= 0 .3)				
Vestibular grade	14,378 (1,929)	14,298 (1,900)	80	0.309
Age	19.64 (3.92)	19.4 (3.92)	0.24	0.157
Gender	0.43 (0.494)	0.42 (0.495)	0.01	0.752
First-semester grades	7.21 (1.45)	7.27 (1.37)	-0.06	0.289
GPA	6.4 (2.14)	6.46 (2.11)	-0.06	0.502

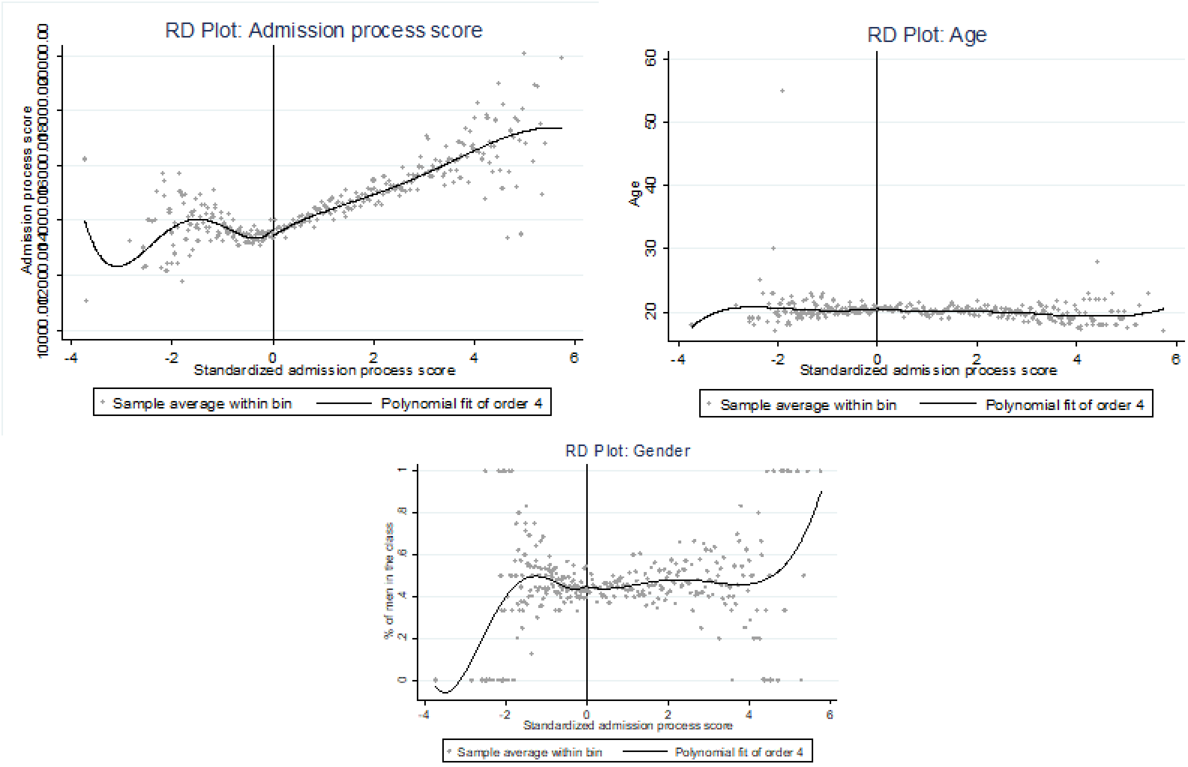
Notes: *Vestibular* is the average grade of students in the Vestibular, in which the maximum grade is 20,000. *Gender* is the percentage of men in the class. *Grades* is the average grade of students in university courses. *GPA* is calculated at the end of the course and corresponds to the grade of the courses weighted by the workload of each course.

Source: authors' compilation based on data from the STI.

In Figure 2 it is possible to observe that there are no discontinuities around the cut-off for the covariates, which indicates that the effect found is not explained by discontinuities in these explanatory covariates. Figure 3 shows some of the discontinuity graphs for the running variable and student performance at UFBA. This is the first evidence of the existence of a discontinuity affecting student performance.[4]

[4] We present here only four graphs, from the 72 regressions estimated.

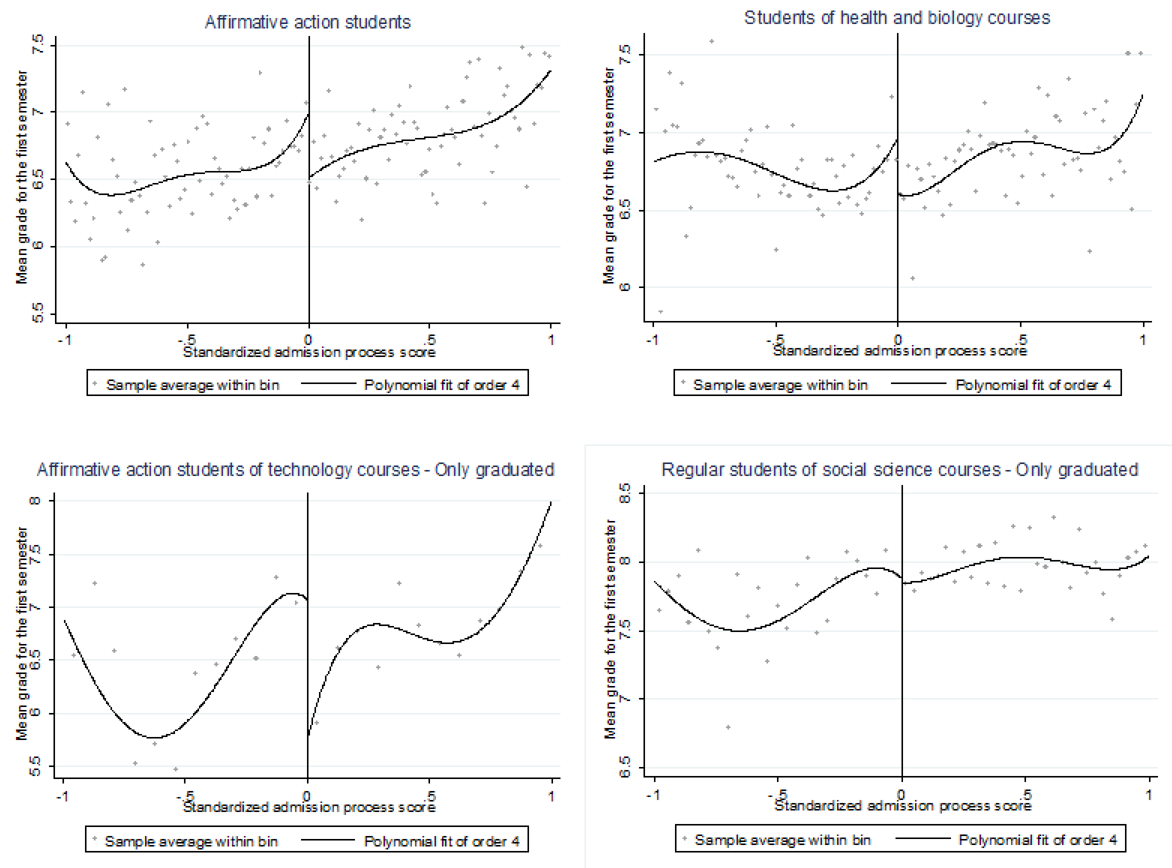
Figure 2: Graphs of individual control variables



Notes: The vertical line at zero is the first-semester cut-off. The dots correspond to the local averages and the line is given by the polynomial fit of order four. The final entrance score is standardized by using the final vestibular score of the last student that entered at the first-semester and the standard deviation of the candidates' scores. Functions are estimated using a triangular kernel with the bandwidth selection procedure proposed by Calonico et al. (2014).

Source: authors' compilation based on data from the STI.

Figure 3: Relationship between the final entrance score at the Vestibular and treatment (mean grade at first semester)



Notes: in total, 72 graphs were generated, one for each outcome and database. Here, we show some of the visual evidence of possible peer effects and/or that were representative for all the databases used. The vertical line at zero is the first-semester cut-off. The dots correspond to the local averages and the line is given by the polynomial fit of order four. The final entrance score is standardized by using the final vestibular score of the last student that entered at the first-semester and the standard deviation of the candidates' scores. Functions are estimated using a triangular kernel with the bandwidth selection procedure proposed by Calonico et al. (2014).

Source: authors' compilation based on data from the STI.

4 Results

4.1 Academic performance

In general, the results indicate that students' rank in the ability distribution of their class may impact their academic achievement, and the estimated effects are larger for Quota students. Panel A in Table 3 shows evidence that the performance of students who entered the university in the first semester (with lower rank within the class) is, on average, worse than the performance of students who entered in the second semester (with higher rank within the class). However, only the estimated parameters for Quota students and/or course graduates are statistically significant. Panel A in Table 3 shows the estimates for all students who started UFBA courses; however, significant effects are found only for Quota students. The results from panel A indicate that Quota students in the first semester (at the bottom of their class's ability distribution) have worse results than students in the second semester (in the middle of their class's ability distribution). Taking column 6 into account, the second-semester students' scores were 0.272 higher than the first-semester students' scores in the first-semester GPA (on a 10-point scale) and this difference is 0.223 in the first-year GPA. We found no significant effects of dropouts.

Table 3: RDD estimates by category

	Non-Quota students			Quota students		
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: all candidates admitted						
First-semester GPA	–0.115	–0.071	–0.063	–0.341***	–0.245**	–0.272***
	(0.089)	(0.086)	(0.077)	(0.116)	(0.105)	(0.1)
First-year GPA	–0.126	–0.087	–0.086	–0.313***	–0.232**	–0.223**
	(0.086)	(0.075)	(0.062)	(0.109)	(0.1)	(0.091)
Dropouts	–0.009	–0.009	–0.009	0.012	0.007	0.003
	(0.01)	(0.01)	(0.01)	(0.018)	(0.017)	(0.017)
Panel B: course graduates only						
First-semester GPA	–0.144*	–0.117	–0.107	–0.393***	–0.343***	–0.289***
	(0.073)	(0.069)	(0.056)	(0.117)	(0.11)	(0.096)
First-year GPA	–0.155**	–0.131*	–0.152***	–0.269***	–0.258***	–0.204***
	(0.081)	(0.076)	(0.065)	(0.096)	(0.098)	(0.074)
Final GPA	–0.158**	–0.122**	–0.132**	–0.269***	–0.242**	–0.201**
	(0.067)	(0.063)	(0.056)	(0.096)	(0.093)	(0.077)
Individual controls	No	Yes	Yes	No	Yes	Yes
Course and year control	No	No	Yes	No	No	Yes

Notes: this table presents the estimated sharp regression discontinuity (RD) at the first-semester cut-off. Panel A includes all applicants admitted and panel B includes only students who have completed graduation. The variables used as individual controls in the (2), (3), (5), and (6) models are age, gender, and admission process score. In models (3) and (6) course and year dummies are included. 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' compilation based on data from the STI.

Panel B shows that when we examine the sample that contains only those students who already concluded the course, the effects in general are greater and the majority of estimates are statistically significant. In this sample, we also found negative effects for non-Quota students to the value of –0.152 in the first-year GPA and –0.132 in the final GPA. The effect for Quota students is very similar to that observed in panel A. However, because panel B contains only students who finished the course, we can verify that this effect is permanent over time, as can be seen in the last row of columns 3 and 6.

4.2 Exploring fields heterogeneity

In Table 4 we split the sample by concentration area: social science, technology, and health and biology. When we analyse all students who started UFBA courses (columns 1, 2, and 3) we found significant effects with a large magnitude for Quota students (panel B), especially for technology courses. Those who were allocated in the first semester (being the worst among the most skilled students) scored 0.845 lower in the first-semester GPA than students who were placed in the middle of the second-semester ability distribution.

Table 4: RDD estimates by concentration areas

Dependent variables	Entire database			Courses Graduates Only		
	Social science	Technology	Health and biology	Social science	Technology	Health and biology
Panel A: non-Quota students						
First-semester GPA	0.254	0.058	–0.125	–0.123	–0.305**	–0.205**
	(0.233)	(0.164)	(0.113)	(0.11)	(0.161)	(0.112)
First-year GPA	0.192	0.091	–0.141	–0.251***	–0.197	–0.172*
	(0.227)	(0.269)	(0.206)	(0.088)	(0.155)	(0.1)
Final GPA	–	–	–	–0.325***	0.023	–0.148*
				(0.114)	(0.147)	(0.091)
Dropout	–0.009	0.024	0.034**	–	–	–
	(0.022)	(0.029)	(0.017)			
Panel B: Quota students						
First-semester GPA	0.087	–0.845***	–0.224	–0.128	–1.275***	–0.085
	(0.178)	(0.312)	(0.147)	(0.197)	(0.328)	(0.131)
First-year GPA	–0.019	–0.581**	–0.21	–0.264*	–0.912***	–0.002
	(0.148)	(0.243)	(0.141)	(0.147)	(0.264)	(0.123)
Final GPA	–	–	–	–0.369**	–0.524***	0.05
				(0.179)	(0.2)	(0.101)
Dropout	–0.061	–0.024	0.013	–	–	–
	(0.043)	(0.05)	(0.039)			

Notes: this table presents the estimated sharp RD at the first-semester cut-off by different concentration areas. The first three columns are the estimates with the entire database and the last three columns estimates only with graduated students. Panel A includes only the regular students and panel B those who were admitted to the university by AA. For all models estimated in this table we included the variables of individual controls. RDs and their relationship with peer quality are estimated using triangular kernels. The bandwidth for entrance score is selected based on Calonicoet 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' compilation based on data.

When analysing only the sample of students who graduated, we found significant effects also for non-Quota students. In panel A we see that, within the non-Quota student group, students who were allocated in the middle of the ability distribution in the first class outperformed those who were in the top of the ability distribution in the second class. This difference is significant for social science courses in the first-year GPA and final GPA, for technology courses in the first-semester GPA, and for health and biology.

In Panel B (columns 4, 5, and 6) it is possible to verify a much stronger negative effect for graduate Quota students of technology courses who entered at the university as the last among the best. This effect, as can be seen in column 5, indicates that the last among the best have average grades that are lower by 1.275 points in the first-semester GPA (on a 10-point scale), 0.912 in the first-year GPA, and 0.524 in the final GPA. These results suggest that peer effects matter more for Quota students in technological courses, which in general require more math knowledge.

4.3 Controlling for teacher fixed effect

In the analysis of the effects of student rank on class skill distribution on the first-semester GPA, we cannot control by fixed teacher effect, since the dependent variable used is an average of the grades obtained at different stages of the courses. To overcome this limitation, subjects with a large number of observations were selected to estimate the same effects as those observed in Tables 3 and 4, but now controlled by a fixed teacher effect. This sample contains only teachers who taught both the first and second classes, which ensures that the methodology will be similar for both groups analysed. The estimates are presented in Table 5. Now we look at each lecture with more than 300 students in the sample.

Table 5: RDD estimates controlling for teacher fixed effect

Classes	Without teacher fixed effect	With teacher fixed effect	Number of obs.	Left of cut-off	Right of cut-off
Calculus A	–2.593**	–2.27***	525	107	85
	(0.797)	(0.68)			
Microbiology	–0.603***	–0.409*	866	200	103
	(0.278)	(0.254)			
Introduction to management	1.764***	1.3***	307	93	56
	(0.626)	(0.434)			
Introduction to biology	–0.783*	–1.014***	434	154	88
	(0.416)	(0.385)			
Civil engineering I	0.251	0.43**	333	79	57
	(0.348)	(0.21)			
Anthropology	1.667***	1.426***	225	46	42
	(0.59)	(0.531)			
Anatomy	–0.524**	–0.461*	760	246	106
	(0.286)	(0.27)			
Biochemistry	–0.335*	–0.576***	818	114	118
	(0.198)	(0.231)			

Notes: this table presents the estimated sharp RD at the first-semester cut-off by different classes. For all models estimated in this table we included the variables of individual controls. 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' compilation based on data from the STI.

Our results show that the effects are similar to those in Tables 3 and 4 for technology and health fields, with the best Quota students of the second semester doing better. In calculus, for example, the results indicate that the last among the best have grades 2.593 lower (on a 10-point scale) in comparison with the Quota students allocated to the second class (in the middle of their class's ability distribution). When we control for teacher fixed effect, the results change to –2.27, which represents 23 per cent of the maximum grade in the lecture. These estimates show, therefore, a very large peer effect for quota students who attend calculus A. The results are very similar for other courses, as can be seen in Table 5.

Another interesting result shown in Table 5 is that, except for the area of health and biology, in classes with no maths in the subject the Quota students of the first semester do better than the quota students of the second semester. This may suggest that these students may be benefiting from the higher average ability of the first class and suffering less from being the least skilled students in the class.

5 Analysis before affirmative action

Before the Quotas policy (2003 and 2004), the candidates were competing for all the available vacancies. Thus, studying this period allows us to evaluate students with similar levels of ability, but who have been allocated to classes in which they are the most skilled or the least skilled. So, using data from before 2005 we are asking the question: is it better to be the first among the last or the last among the first?

Importantly, prior to AA, most of the students occupying the available places were from private schools. Before AA, about 77 per cent of individuals entering UFBA studied exclusively in private schools, 10 per cent had part of their studies at private schools, and only 13 per cent studied exclusively at public schools. Since 2005, with the implementation of quotas, 45 per cent of the vacancies have been reserved exclusively for students of public schools. This implies that students who under the current criteria would be classified as Quota students were very unlikely to have been able to enter university before AA. What explains this fact is that, in Brazil, the quality of the public school system is much lower than that of private schools. Thus, when analysing the period prior to 2005, we are using a group of students mostly from private schools and with characteristics closer to the group of students who entered without AA after 2004.

Table 6 displays the results for the estimations of RDD using students who entered in 2003 and 2004. The first column shows the estimate using all students who entered the university, regardless of the area of knowledge. The results show that there is no significant difference between being the most skilled of the second class or the least skilled in the first class.

Table 6: RDD estimates without AA (2003–04)

Dependent variables	All students	Social science	Technology	Health and biology
Panel A: all candidates admitted				
First-semester GPA	–0.303	–0.757	0.136	–0.785 **
	(0.333)	(0.393)	(0.707)	(0.392)
First-year GPA	–0.173	–0.634	–0.012	–0.539
	(0.298)	(0.42)	(0.751)	(0.302)
Dropout	–0.027	0.029	–0.194	–0.14
	(0.059)	(0.127)	(0.189)	(0.199)
Panel B: course graduates only				
First-semester GPA	–0.189	–0.518	0.171	–0.642**
	(0.275)	(0.306)	(0.774)	(0.334)
First-year GPA	–0.199	–0.516	–0.171	–0.386*
	(0.263)	(0.299)	(0.827)	(0.209)
Final GPA	–0.228	–0.475	0.071	–0.254
	(0.268)	(0.502)	(0.691)	(0.244)

Notes: this table presents the estimated sharp RD at the first-semester cut-off. Panel A includes all applicants admitted and Panel B includes only students who have completed graduation. The variables used as controls in the models are age, gender, and admission process score. 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' compilation based on data from the STI.

Columns 2, 3, and 4 show the results for each subject area (social science, technology, and health and biology courses). We note that there is only a significant effect for students in the health and biology area. The result suggests that being the most skilled in the second semester group implies a better performance at university than being in the last of the first-semester class.

5.1 Labour market

The greatest limitation of the previous subsections is our inability to ensure that the effect found is only explained by peer effect, without teachers changing the level of the classes between semesters. However, when we look only at the labour market there is no teacher effect anymore. In this sense, the only explanations for differences in students around the cut-off is the classes that they were assigned and, consequently, their peers.

In general, the results presented in Table 7 show no effects of being assigned to the first class on the probability of having a formal job. However, there is a positive effects on wages for Quota students. This suggest that Quota students can benefit from having better peers in terms of the labour market.

In Table 8 we present the estimates of impact on wages by graduation year. First we compare every student that appears in the labour market and then we compare only those that start working after graduation. The results suggest that the effect is positive for Quota students and negative for non-Quota students. This means that when we look at the labour market, the last Quota students of the first semester positively benefit from their peers, probably influenced by the networking created during their time at university. However, the opposite effect is found for non-Quota students.

When we look at the estimations and split the sample by subjects, in Table 9, we observe that Quota students from the technology field had lower probability of being employed. This result could be related to the strong results of lower academic performance for this group. This suggests that lower academic achievement for this group (technology Quota students who were allocated at the bottom of their class ability distribution) could be associated with worse labour markets outcomes. Otherwise, the negative effects for wages for non-Quota students and the positive effects for Quota students seem to be explained for movements in technology and social sciences, respectively.

Table 7: Estimating the impacts on labour market outcomes

Subject	Basic	With controls	Controlling for starting date	Basic	With controls	Controlling for starting date
Panel A: non-Quotas						
	Outcome: being employed			*Outcome: log wage*		
First-semester cut-off	0.0221 (0.0181)	0.0221 (0.0181)	0.0289 (0.0267)	–0.111* (0.0449)	–0.0128 (0.0396)	-0.0158 (0.0349)
Observations	10,320	10,320	8,470	8,529	8,448	7,620
Panel B: Quotas						
First-semester cut-off	–0.00688 (0.01953)	0.00718 (0.01785)	0.01588 (0.03491)	0.188** (0.0725)	0.142*** (0.0320)	0.04154 (0.04536)
Observations	12,143	12,143	7,385	10,560	10,459	5,721

Notes: this table presents the estimated sharp RD at the first-semester cut-off. For all models estimated in this table we included the variables of individual controls. 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' compilation based on data from the STI.

Table 8: Estimating the impacts on wages by graduation year

Panel A: non-Quotas								
Variables	2010	2011	2012	2013	2014	2015	2016	2017
First-semester cut-off	–0.162 (0.198)	0.026 (0.127)	–0.463*** (0.123)	–0.294** (0.109)	–0.128 (0.159)	–0.347** (0.111)	0.0811 (0.147)	–0.919*** (0.209)
Observations	955	1158	1006	1169	1235	1112	967	582
Keeping only people that started working after graduation								
First-semester cut-off	–0.0372 (0.139)	–0.168 (0.118)	–0.0569 (0.103)	–0.0162 (0.109)	0.415*** (0.0896)	–0.103 (0.0768)	–0.275** (0.101)	–0.668*** (0.161)
Observations	944	1,149	1,002	1,164	1,231	1,104	956	556
Panel B: Quotas								
First-semester cut-off	0.0474 (0.111)	0.743*** (0.119)	0.790*** (0.123)	0.143 (0.0811)	0.112 (0.106)	–0.0606 (0.143)	0.351** (0.117)	0.0564 (0.116)
Observations	1,012	1,163	1,165	1,536	1,662	1,501	1,298	774
Keeping only people that started working after graduation								
First-semester cut-off	–0.138 (0.0924)	1.025*** (0.165)	0.679*** (0.119)	0.185 (0.099)	–0.0823 (0.14)	–0.294 (0.201)	–0.086 (0.208)	–0.0385 (0.385)
Observations	756	820	811	1,004	982	617	339	106

Notes: this table presents the estimated sharp RD at the first-semester cut-off. For all models estimated in this table we included the variables of individual controls. 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' compilation based on data from the STI.

Table 9: Estimating the impacts on labour market outcomes by fields

Subject	Social science	Technology	Health and biology	Social science	Technology	Health and biology
Panel A: non-Quotas						
	Outcome: being employed			*Outcome: log wage*		
First-semester cut-off	–0.0151	–0.0103	0.0924*	0.00745	–0.476***	0.117
	(0.0208)	(0.0625)	(0.0455)	(0.0462)	(0.112)	(0.0756)
Observations	4,543	1,053	2,282	4,245	715	1,443
Panel B: Quotas						
First-semester cut-off	0.0147	–0.378**	0.0102	0.466***	0.234	–0.165
	(0.0198)	(0.122)	(0.0562)	(0.0636)	(0.18)	(0.104)
Observations	5,591	954	2,724	5,380	665	1,885

Notes: this table presents the estimated sharp RD at the first-semester cut-off. For all models estimated in this table we included the variables of individual controls. 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' compilation based on data from the STI.

6 Conclusion

The objective of the present study was to analyse whether the allocation of students to different positions in the ability distribution of their class can influence their performance at UFBA and their labour market outcomes. In general, the estimates in academic performance indicate that worse student rank in the ability distribution of their class may negatively impact their academic achievement, and the estimated effects are larger and more significant for Quota students. This evidence was found for the analyses of the average grades at first semester, first year, and GPA, with varying magnitude depending on the estimated equation or the database used. This effect is stronger when analysing only Quota students and the subject of technology.

The results presented in Tables 3 and 4 raise two discussions. The first is the peer pressure literature, where the most skilful peers can exert negative pressures on the behaviour of less-skilled students. More specifically, the 'worst student' in the first semester class may feel unable to keep pace with his or her peers, reducing their efforts in disciplinary activities. These students may feel too embarrassed to publicly participate in discipline activities or to question their most skilled colleagues so that their difficulties are not perceived by others. The second is the signalling that the best students give to the teacher, so that the teacher may not perceive the difficulty that the lower-ability students have in following the discipline, so they conduct their classes with a focus on those who have the easiest learning. These effects are important at a basic education level (Duflo et al. 2011) and probably could affect college students.

The results corroborate the studies for the Federal University of Ceará and the Federal University of Pernambuco, which are in the second and third largest states of the Brazilian Northeast in terms of per capita income. In addition, the results also interact with the work of Foster and Frijters (2010), who applied a questionnaire to 1,733 Australian students about their perception of peer effects. They sought to identify whether the students believed that studying with more skilled and/or struggling peers could influence their own learning and effort. It was observed that most students believe that their peers have a great impact on their performance and/or behaviour at university, and the more skilled students believe, on average, that this effect is greater.

In this sense, our results are in agreement with the peer effects literature and the hypothesis of homophily of Carrell et al. (2013)—that is, the tendency of individuals to relate to other individuals with similar characteristics. Increasing the average ability in a class may cause students of lower ability to isolate themselves in a subgroup, making their grades converge to a lower value.

An important issue is that the difference in performance could be driven by peer effects or teacher behaviour. In the Table 5 we tried to overcome this problem and show that the result does not change with the inclusion of teacher fixed effects. In Table 10 we show that when we control for skill and socio-economic characteristics, there is no significant mean difference between the two classes for technology and social science courses. That is, there is no evidence that teachers grade on a curve for courses in these areas of concentration, which are the main results of this paper.

Despite the advances made to guarantee access of the needy population to university, UFBA also must move towards the discussion of the policies that allow lower-ability students to understand the courses and overcome the knowledge deficiencies of these students from poor backgrounds. UFBA itself already carries out some policies, such as research grants for Quota students (Programa Permancer) and aid for food and housing. However, there are no policies aimed at correcting the deficiency that these students carry forward from the poor quality of public education in Brazil. In this way, the results found suggest the need for this type of discussion in the university's policy agenda, especially in the Quota community studying in the technology field.

Table 10: Grade difference between classes

	Social science	Technology	Health and biology
Quota and non-Quota students	0.03	–0.047	–0.075*
	(0.049)	(0.072)	(0.042)
Quota students	0.155**	0.068	–0.056
	(0.08)	(0.13)	(0.076)
Non-quota students	0.005	–0.022	–0.119**
	(0.071)	(0.093)	(0.052)

Notes: this table shows the mean difference between the first class and the second class, controlling for ability, socio-economic characteristics, course, and year. A non-significant result means that the average class skill has no significant impact on the students' grades in that class; a positive result implies evidence of positive peer effects; and a negative result would be evidence that teachers grade on a curve, or negative peer effects.

Source: authors' compilation based on data from the STI.

Finally, the results of class assignment on labour market strongly differ if the students are Quota or non-Quota students. In general, the results suggest that being among the best is beneficial for Quota students, but the opposite effect is found for non-Quota students. Interesting, the only effect that we found on the probability of being employed is a negative effect for the Quotas students from the technological field, which suggests a strong correlation between lower academic performance and worse labour market outcomes.

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Appendix

Table A1: UFBA's courses with two entries in the year

Social science	Technology	Health and biology
Management	Biotechnology	Computer science
Law	Physiotherapy	Civil engineering
Social science	Speech therapy	Electrical engineering
Accountability	Medicine	Mechanical engineering
Communication	chemistry	
Pedagogy	Biology	
Executive secretariat	Nursing	
Social service	Nutrition	
	Dentistry	
	Zootechnics	
	Medicine veterinary	