Peer Effects and Academic Performance in Higher Education - A Regression Discontinuity Design Approach

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Abstract

We estimated peer effects in undergraduate students' academic performance at a Brazilian university. Our empirical evidence comes from a micro data set containing information of 1550 undergraduate students enrolled in 27 courses at the Federal University of Ceará. In light of this great courses availability, we assign each course into one of four categories depending on its admited students' results at the entrance exam. Then, we proceed the estimation exercise using a multi-treatment effect model. In this fashion, using IRA as a measure of academic performance, we obtain a negative effect (-0.19) for being in a first semester class, which means a 2% smaller IRA for firt semester students, *vis-a-vis* members of second semester classes. Moreover, we found non-linearities in this effect, since, for example, it ranges between 0.5 to -0.18. This results are in accordance with Sacerdote (2001) and Zimmerman (2003), also finding non-linearities in "peer effects".

Keywords: Peer Effects, High Education and Regression Discontinuity Design
JEL Codes: J24, I23 and C21

1 Introduction

Human beings are social creatures. This is based not only on the fact that we like company or depend on each other. Human beings are social creatures simply in the sense that our existence requires interaction with other people (Gawande n.d). In the last decades, economists have devoted great attention to these interactions and its influence on individual behavior. The effects of these interactions are known in the literature as "peer effects".

Sacerdote (2011) defines peer effect as any externality, excluding those market-based or price-based, in which peers' background, current behavior, or outcomes exert an influence on a specific outcome obtained by another individual. Manski (1993) classifies this effect as endogenous, when it emanates from peers' current outcomes, and exogenous, when it is due to peers' backgrounds.

Several studies have analyzed peers' influence on criminal activity, drugs use, teenage pregnancy, educational achievement, among others (Sacerdote 2011). Looking specifically at the literature concerning educational achievement, peer effects have played an important role for primary and secondary education since Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld, and York (1966) seminal work, being considered a key factor in determining children's schooling outcomes (Winston and Zimmerman 2004).

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Even though the importance of peer effects in elementary and secondary education had been raised a long time ago, its relevance to the economics of undergraduate/graduate degrees has only recently been acknowledged (Winston and Zimmerman 2004). Thenceforward, this research agenda experimented an exponential growth, with several studies seeking to take a deeper look at the peer effects for higher education. So far, the empirical results bring up contradictory conclusions. Some studies find a positive effect on academic outcomes due to peers' influence, while others show negative effects or even no effect at all (Epple and Romano 2011, Sacerdote 2011).

Commonly, the literature has been using roommates interaction as a standard source of peer effects. This is the case for works such as Sacerdote (2001),Zimmerman (2003) and McEwan and Soderberg (2006). On the other hand, studies like De Paola and Scoppa (2010), Androushchak, Poldin, and Yudkevich (2012) and Booij, Leuven, and Oosterbeek (2015) prefer to take advantage of classmates interactions. Our paper follows this guidance and uses the interactions between classmates as well. However, it contributes to the literature presenting a different group formation.

Based on this set of papers, we believe our endeavor has its own merits. Firstly, we estimate peer effects in higher education for a developing country with an institutional background which is very different from what is found in OECD members, for example. Secondly, by aggregating new methodological procedures, we can better understand the relation between peer effects and academic performance in high education.

Therefore, this paper aims to estimate peer effects of undergraduate students on academic outcomes. For this purpose, we used a micro data set conceded by the Federal University of Ceará, a public Brazilian university located in Fortaleza, the capital city of Ceará. Our data set brings several socioeconomic information and maps concerning 4 years of academic performance with respect to 2149 students enrolled in 33 undergraduate programs. Due to the entrance process specificities, we are able to estimate peer effects using a sharp regression discontinuity design. Also, in light of programs' heterogeneity, and since the assignment grade distribution pattern is different, we are able to estimate a multi-treatment effect model. For this, we classify each program according to the competition in its first and second semester classes.

We found that peer effects have a negative impact on the academic performance of our undergraduate students. The evidence suggests that low-ranked students put together with high-ranked classmates have a worse academic performance than those in a lower level class. This goes against several studies of peer effects for primary and high schools, as well as for higher education.

Notwithstanding, for a multi treatment model, we also found evidence of non-linearities as in Sacerdote (2001) and Zimmerman (2003). We found positive peer effects when both first and second semester classes are of low competition level, and negative peer effects in all other configurations, with modest magnitudes when both classes are of high competition level.

Besides this introduction and a final considerations section, this paper presents five more sections. Section 2 offers a brief literature review of peer effects on academic outcomes. Section 3 introduces the entrance process for Brazilian universities and demonstrates that it follows a sharp design. Section 4 scrutinizes our data, presenting the results of an initial exploratory analysis. Section 5 sets up the model to be estimated and a brief discussion of the estimation method. Finally, section 6 presents our results.

2 Brief empirical literature review

2.1 Peer effects

The literature of peer effect on academic achievement has grown significantly in recent years. Studies trying to access its role in elementary, secondary and post-secondary educational levels are of particular interest in many countries, raising different methodological approaches to take the particularities of each educational level and backgrounds into account.

Sacerdote (2001) estimated peer effects among Dartmouth College (USA) roommates. He found that peers have an important impact on students' grades and on the decision to join social groups such as fraternities. Also, the paper attests a non-linearity in these peer effects: students whose roommates were in the top 25% of the class had higher grades. Sacerdote (2001) concluded that high-ability students had a positive effect on the academic achievement of relatively less talented colleagues, while there was no such influence for students in the middle of distribution.

Similarly, Zimmerman (2003) studied peer effects among Williams College (USA) undergraduate students. In this paper, since first year roommates were assigned randomly with respect to academic ability, the author could estimate differences in grades of high, medium, and low SAT students living with high, medium or low SAT roommates. The results indicated that a medium student tended to have worse grades if put together with a low SAT roommate, while high ability students were least influenced by peers.

McEwan and Soderberg (2006), in a study carried out at Wellesley College (USA), estimated the effects of students' background characteristics on their roommates' academic outcomes. The authors applied both a linear and a nonlinear model. Regarding the first structure, there is no evidence of peer effects on students' GPA. With respect to the nonlinear specification, the results suggest that students' SAT scores have a nonlinear effect on their roommates' achievement, yet the results are not robust. The conclusion is that there might exist roommate peer effects restricted to a small number of students. However this effect is not a key determinant for academic outcomes.

Carrell, Fullerton, and West (2008) also estimated peer effects in college achievement. The paper uses data from the United States Air Force Academy, in a context in which students are exogenously assigned to peer groups. The interaction is even stronger in this case, since required activities involve both academic and non-academic duties. They find a scholarly peer influence larger than those found in previous studies relating to roommates. Furthermore, peer effect persists at a diminishing rate into sophomore, junior, and senior years, indicating long lasting ties on academic achievement.

Contreras, Badua, and Adrian (2012) investigated peer effects for classroom colleagues in a Business College of a U.S. public university. The authors find a negative significant peer effect in students' performance, yet the proper direction and magnitude are sensitive to both peers' and student's own average ability.

Besides the USA, there is a growing literature in European countries on peer effects. In Italy, De Paola and Scoppa (2010) analyzed peer effects among students of Calabria University, a middle-sized public university. They found a positive and statistically significant influence, being robust to different peer group definitions and abilities measures. Also, the effect was larger than previous studies focusing on roommates. The results attest that students' ability is an important input in college education, which means that attracting high-level students is a key path to improve the overall performance by means of direct and indirect directions.

Androushchak, Poldin, and Yudkevich (2012) used data about Russian undergraduate students enrolled at the Economics department of the National Research University — Higher School of Economics (HSE)— to estimate peer effects in exogenously formed groups. The evidence suggests that high-ability classmates exert a positive influence on individual academic performances. Still, the most talented ones are the greatest beneficiaries from this presence. The paper also finds that an increase in the proportion of low-performance students has an insignificant or negative influence on individual grades.

Regarding undergraduate students in Economics at the University of Amsterdam (NED), Booij, Leuven, and Oosterbeek (2015) estimated peer effects from tutorial groups' ability composition. Aiming to achieve a wide range of support, the authors manipulated these compositions and assigned the students randomly. They find that low and medium ability students gain, on average, 0.2 standard deviation achievement units after switching from ability mixing to three-way tracking — a system in which each group is constituted by students of the same ability distribution, measured by GPA. They also find that high-ability students are not affected by the specific group composition, and defend that there is no evidence implying that teachers adjust their teaching to different group configurations.

2.2 The use of regression discontinuity design

In common, none of these papers use a regression discontinuity design approach to estimate peer effects in academic achievement. Actually, this approach is usually found in analysis of both remedial education effects and financial aid on academic achievement, due to particularities of post-secondary educational level.

Moss and Yeaton (2006) are an example of a sharp regression discontinuity design application in remedial education. This study analyzed the effectiveness of a developmental English program in an American university. The program offers compulsory remedial education to students of ASSET scores less or equal to 85 out of 107 points. The authors found that those students participating in the program had their English academic achievement similar to those initially out of supplemental coursework. Furthermore, the students in greatest need of the program had the major benefit from it.

Another example is the study of Butcher, McEwan, and Taylor (2010). It estimated the causal effect of taking a course in quantitative reasoning on student's academic performance and classroom peer-group composition at Wellesley College (USA). The assignment rule in this program is similar to the one presented in Moss and Yeaton (2006): if the student's test score is less or equal to 9 (out of 18), then he/she is assigned to this mandatory quantitative course. The authors found that there is no impact in taking the course on student's academic outcomes. Nevertheless, they identified robust effects on classroom peer-group composition, i.e, classmates of this remedial course tend to keep studying together along other different courses.

In a similar study, Schöer and Shepherd (2013) estimated the role of taking a compulsory remedial course on students' performance in an undergraduate level microeconomics class. Using data from a South African university, they used a fuzzy regression discontinuity design and found that this program participation positively affects students' performance.

Regarding the role of financial aid on academic outcomes, the seminal paper of Van der Klaauw (2002) analyzed the effects of universities' financial aid offers on students enrollment decisions. The author found that this recruitment resource is an effective instrument in competing with other colleges for new students. In the same line, Leeds and DesJardins (2014) found similar conclusions for the University of Iowa. In addition, the results suggest that financial aids may have strong effects on the brightest candidates.

Mealli and Rampichini (2012) analyze the relation between grants offered by an Italian university for low-income students and their dropout decision. The results suggest that, at a given threshold, the grant is an effective tool to prevent those low-income students to drop out of higher education. However, if the family income is much lower than this threshold, then the grant effect becomes smaller and not significant.

Canton and Blom (2004) analyzed the effects of financial aid on enrollment and students' performance at Mexican universities. The results indicate a positive effect for both issues. Concerning the enrollments, a strong impact is verified, since the probability of entering in higher education is raised in 24 percent. For the performances, students who receive financial aid have better academic results than those without it. A similar study was carried out by Curs and Harper (2012), attesting that students who receive financial aid have a GPA between 0.12 and 0.16 higher than students who do not.

In the studies of peer effects, the methodological framework depicted by the regression discontinuity design is more usual when dealing with elementary and high school levels. For example, Foureaux Koppensteiner (2012), using Brazilian data on elementary school students, estimated the effect of being in a class of older classmates on students' achievement. The conclusion consists in a large negative impact of it. Card and Giuliano (2015) estimated the effect of being in a gifted/high achiever classroom for U.S. students. They found positive and significant effects concentrated among minorities, and found no evidence of spillovers on non-participants of the program.

The same Card and Giuliano (2015) motivation is presented in Vardardottir (2013). Refering to high school Icelander students, this paper estimated the effect of being in high-ability classes, and found a significant and sizable positive impact on the academic achievement of students around the assignment threshold. Abdulkadiroğlu, Angrist, and Pathak (2014) are also concerned about peer effects at a high school level. They estimated the effect of study in a high-quality school, and the results suggest that the marked changes in peer characteristics at exam school admissions cutoffs have little causal effect on test scores or college quality.

In common, all of these studies follow a clear rule in the class group formations, which are usually not the case for U.S. and European universities. With respect to Brazil, there is a well-established rule in forming two types of undergraduate classes: the first one gets the best ranked students in the entrance process, and start academic activities in February (first semester); the second type is a place for the lowest ranked students, and runs at the beginning of August (second semester). Relying on this fact, we developed our study.

3 The entrance process in Brazilian universities

In Brazil, according to de Estudos e Pesquisas Educacionais Anísio Teixeira (Inep) (2014), in 2013, there were 7,3 million students enrolled in 2,391 higher education institutions. Among those institutions, 106 are public and maintained by the Brazilian federal government, counting 5.968 undergraduate programs and 1,14 million students enrolled at federal institutions. In other terms, these numbers represent 18% and 15% of Brazilian undergraduate programs and college students, respectively.

Since federal universities are free of charge and present a high teaching quality[1], they are target of many students from all social backgrounds, which translates into a high demand and, therefore, great competition for a vacancy. Thus, in order to ensure equal access, its entrance processes take place by means of a public tender.

Silva (2007) makes a historical analysis of the admission process in higher education in Brazil. In the 19th century, students who aimed to enter in higher education had to go through a series of tests after they completed the secondary education to obtain a required grade to access the higher education. These exams were called exit tests.

From 1915 on, these exams became to be called *Vestibular*, as we know nowadays, being mandatory for all students who wanted to access the higher education system. This admission process became effective, in fact, in the 1920s, when the number of candidates became higher than the number of vacancies. In this period, *Vestibular* still was an exit test.

It was after 1925 that *Vestibular* became an entry test, whose objective was to evaluate student's capability to understand studies at higher level. The exams were restricted to disciplines considered pre-requisites to the undergraduate program the student intended to attend to.

In 1971, due to the pressure of the students who were unable to access higher education, new conditions of access were created. This new system established that *Vestibular* must have only one content for all programs and adopt classification criteria, in which students that obtained the greatest grades were selected. Under this system, each university became responsible to organize its own selection process, establishing the number of vacancies to be offered (Silva 2007). This system remained in force until 2010, when a new admission process based on ENEM and SISU arose[2].

[1] In Brazil, public universities hold status of higher quality compared to their private counterparts.

[2] Since 2011, the new entrance process is by means of ENEM and SISU. Students take a centralized national exam (ENEM) and, in light of the obtained results, they choose any university and undergraduate program (SISU), taking their own score and the cutoff score determined by competition into account.

Abreu (2013) summarizes *Vestibular's* algorithm. In a first moment, each student chooses and announces only one program of his preference. In a second moment, for each program, a preference relation is determined, utilizing the grade obtained in the exam. And finally, students are allocated based on their rankings and preferences of the chosen program. It was demonstrated that this algorithm is not stable, is not pareto efficient and is not strategy-proof.

At the time of our analysis, the Federal University which we have access to the information used *Vestibular* as its admission process. In this University, the exam consists in two stages. The access to the second stage is conditioned by the performance in the first stage. All students above a rank at the first stage exam are accepted to the second stage, which make the number of students who take the second stage exam a multiple (usually 4 sometimes 3) of the number of final available vacancies. These ranks (one for each major) define a first stage grade threshold. Similarly, second stage threshold determine who passes the exam and enters the University (Carvalho, Magnac, and Xiong 2014). Based on scores achieved in the second stage, students were ranked, vacancies were filled, and the upper classified half of students for every course was assigned to start studies in the first semester of the academic year (first semester class), while the bottom half was allocated into the second semester(second semester class).

Carvalho, Magnac, and Xiong (2014) demonstrated that this threshold is a Bayesian Nash equilibrium, and it is unique. This allows us to use a sharp regression discontinuity design to analyze peer effects among students allocated in first semester classes and in second semester classes.

4 Data

Our analysis is based on a rich administrative data set, providing information on undergraduate students enrolled in 2008 at the Federal University of Ceará (UFC). This is a public Brazilian university located in Fortaleza — the fifth largest city in Brazil with a population of 2.5 million citizens. Founded in 1954, UFC is considered one of the best universities in Brazil according to the Brazilian ministry of education, and the second best in the northeastern region. During the 2013 academic year, the university had 26,782 students enrolled in 114 undergraduate programs. With respect to graduate programs, the university had 6,061 students enrolled in 167 programs, divided into *lato sensu*, professional and academic masters, as well as doctoral programs. The Federal University of Ceará was constituted by 2,152 professors, of whom 1,436 and 543 have doctoral and master's degrees, respectively. UFC also had 3,407 administrative staff members, including the University Hospital (University 2014).

The data set was collected from both the Vestibular Commission and the provost Office of Undergraduate Studies. We have information on 27 undergraduate programs with classes starting in both academic terms[3], counting 1550 students. Our data covers grades and final classification in the entrance exam for the 2008 academic year. We also bring information on the students' socioeconomic characteristics, collected at the registration stage by means of a survey held by the Vestibular commission. Concerning academic performance, students are traced from 2008 to 2011[4], which is equivalent to 8 academic semesters and to the required time before graduating. As a measure of academic achievement, we use IRA — UFC equivalent to the American GPA.

The IRA (Índice de Rendimento Acadêmico) index is a measure of student's academic performance similar to the American GPA, but in a 10-point scale. This index is used to rank students for research and teaching grants, for distinction purposes and so on. The IRA index for a student i is calculated as follows:

[3]This is equivalent to 38% of the total amount of undergraduate programs.

[4]Or until student drops out the course.

$$IRA_i = \left(1 - 0.5\frac{T}{C}\right) \times \left(\frac{\sum_j P_i \times C_j \times N_j}{\sum_j P_j \times C_j}\right) \tag{1}$$

Where:

- T is the sum of all withdrawn courses' workload;
- C is the sum of all courses' workload, withdrawn or not;
- C_j is the workload of course j;
- N_j is the final grade of course j;
- P_j is the period in which the course was done, obeying the following limitation: $P_j = \min\{6,$ semester in which the course was done$\}$.

As shown above, the IRA index is a weighted mean. Variable $\frac{T}{C}$ measures the proportion of all withdrawn courses' workload with respect to the total amount (withdrawn or not). Note that it has a negative impact on the IRA index, i.e, when this proportion becomes higher, the IRA index turns lower. So, the withdrawal of any course is penalized with a reduction of the student's IRA index.

When it comes to courses concluded, some important comments should be made. Firstly, if a course is attended more than once, which is the case for failures, the same number of times appearing in the student's transcript of records will be included in the IRA index calculation. Secondly, in case of course failure by attendance, the final grade will be zero. Table 1 presents the variables used in this paper.

Table 1: Variables descriptions

Variable	Description
IRA	Student's academic index
SAG	Standard student's grade obtained in the Vestibular exam
Age	In years
Gender	1 if student is male; 0 if female
Log(income)	In R$

Source: Elaborated by the Authors

From table 1, variable *SAG* deserves special attention. We defined it as the difference between student's final grade in vestibular and that of the last ranked student within the same semester class — i.e. the class cutoff grade — divided by the standard deviation of the student's course. This procedure helps us to have all first semester students with positive *SAG*, while second semester students will have it negatively, with *zero* as its cutoff. In summary, all courses will have the same cutoff now.

Table 2: Descriptive statistics

Variable	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev	N
	Full Sample			First Semester			Second Semester		
IRA	7.8307	1.3208	12400	7.9690	1.2408	5992	7.7014	1.3790	6408
SAG	0.1722	0.9779	1550	0.9562	0.8191	749	-0.5609	0.3328	801
Age	19.0316	2.9165	1550	18.8051	2.4943	749	19.2434	3.2495	801
Gender	0.4406	0.4966	1550	0.4419	0.4969	749	0.4395	0.4966	801
Log(income)	7.4835	1.0105	1550	7.5025	1.1091	749	7.4657	0.9090	801

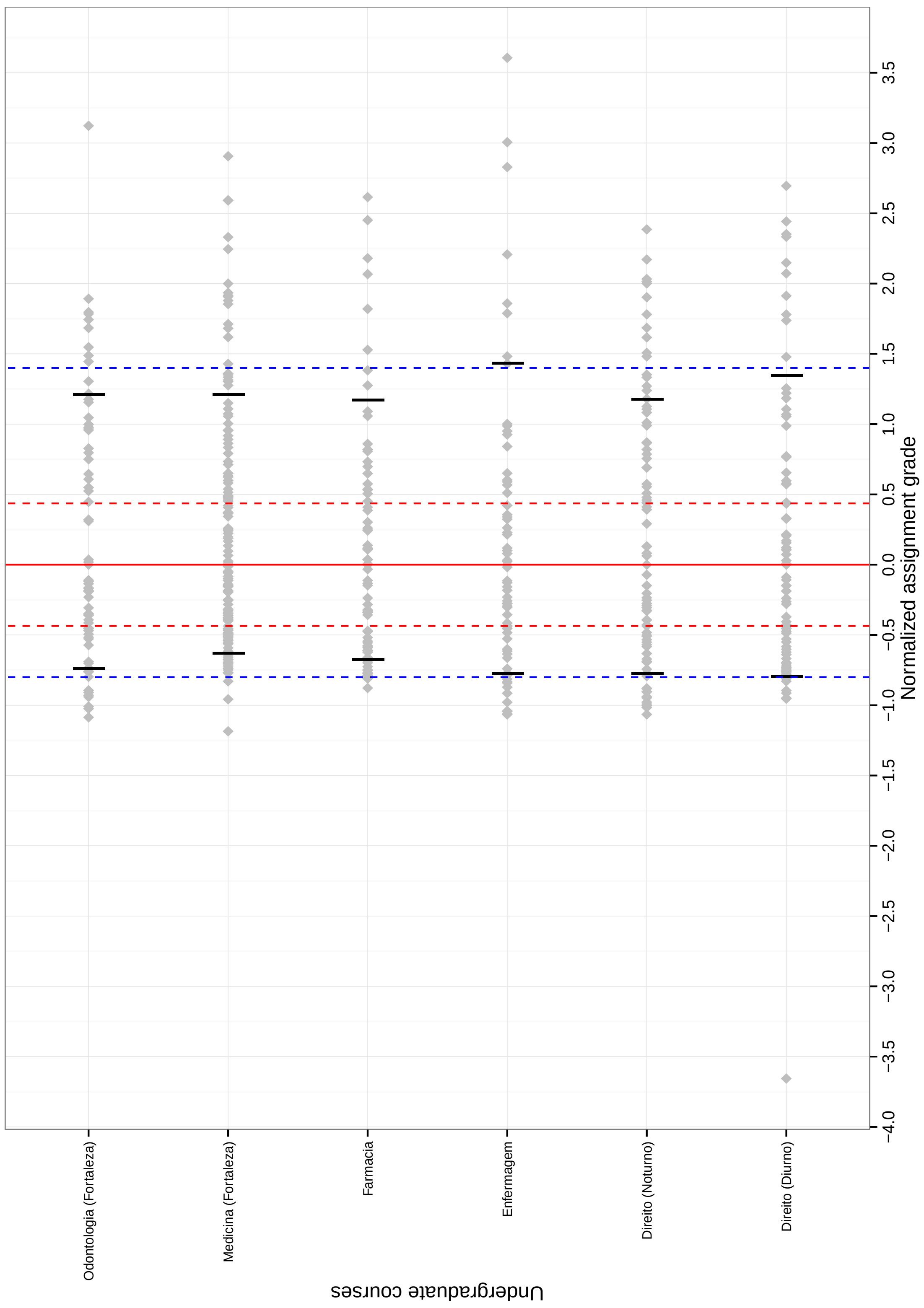
Source: Elaborated by the Authors
Note: N differs in IRA because there were students who dropped out the course.

Table 2 shows the socioeconomic profile and academic performance of our students. The first three columns relate to the full sample. We can see that 44% of the students are males, with average age and log(income) equal to 19.03 and 7.4835, respectively. The average of students' academic performance, measured by IRA, equals 7.8307. Finally, the average SAG is 0.1722.

Now, looking at first and second semester classes, we can see that these two groups have similar socioeconomic characteristics. Note that both are composed by approximately 44% of males with 19 years old and a log(income) of 7.5 and 7.46, for the first and second group, respectively, in average. The academic performance of the first semester group is 7.96, and 7.70 to the second.

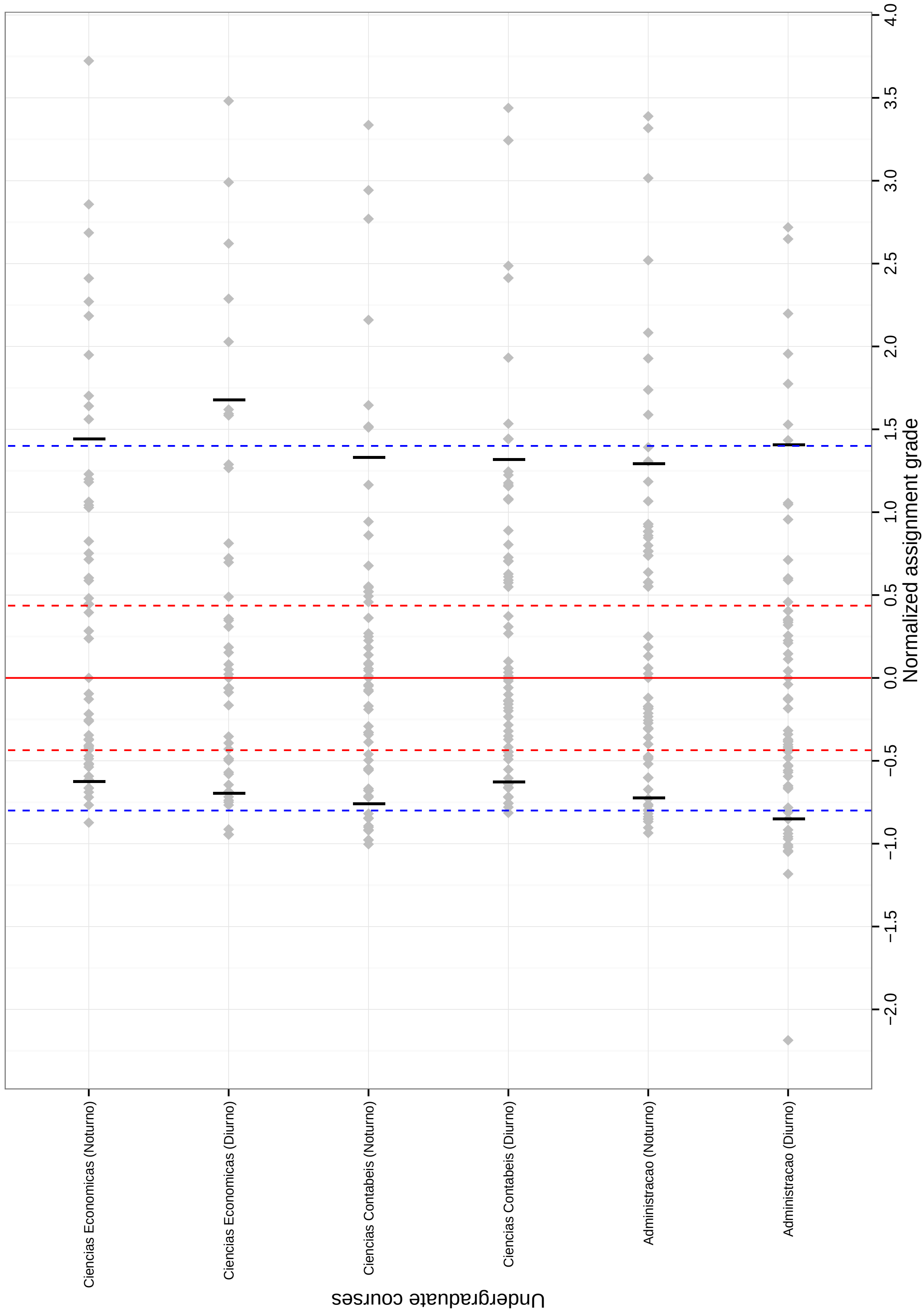
Finally, by definition, variable SAG has a positive or negative sign depending on the reference class — first or second semester, respectively. Concerning the spread of SAG, the standard deviation in the first group is larger than in the second, which shows that the class beginning in the last academic semester is more homogeneous. This is not a coincidence, since students ranked in the top class tend to be more prepared and achieve higher grades in vestibular. It also involves the top 1% students, whose grades are possibly too far from average. We can see this better in figures 1, 2, 3, 4 and 5.

Figure 1: Distribution of normalized assignment grade by courses - Medical school and Law school



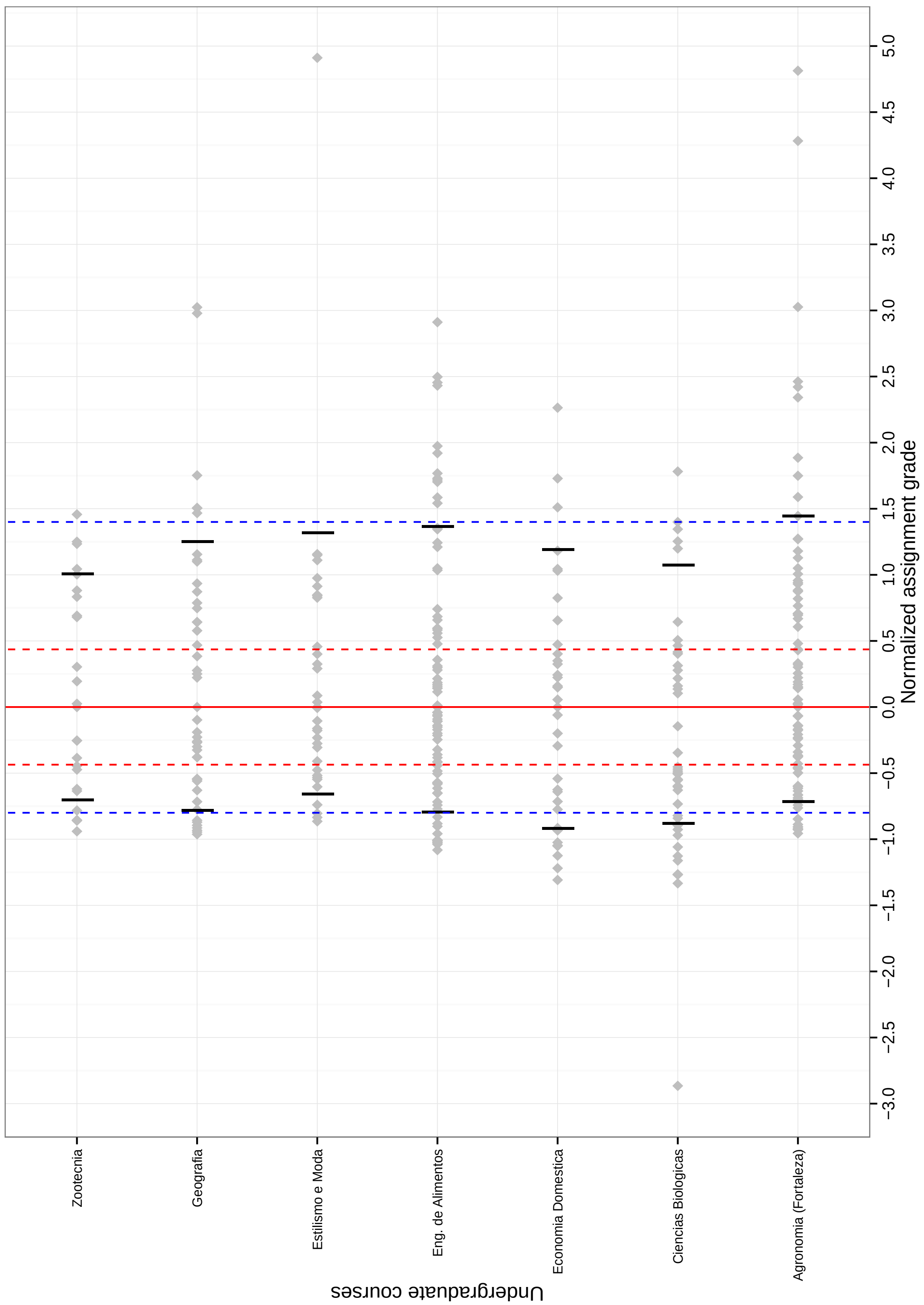
These figures display the SAG distribution for each course. Figures 1, 2, 3 and 4 present the courses separated by academic units, while 5 shows all courses. Points relate to individual observations, while bars represent the average SAG in each class. We can clearly see heterogeneity in SAG distributions. For example, courses like ***Ciencias Economicas (Diurno)*** (2) have a high SAG average

Figure 2: Distribution of normalized assignment grade by courses - College of Economics, Management, Actuarial Science and Accounting



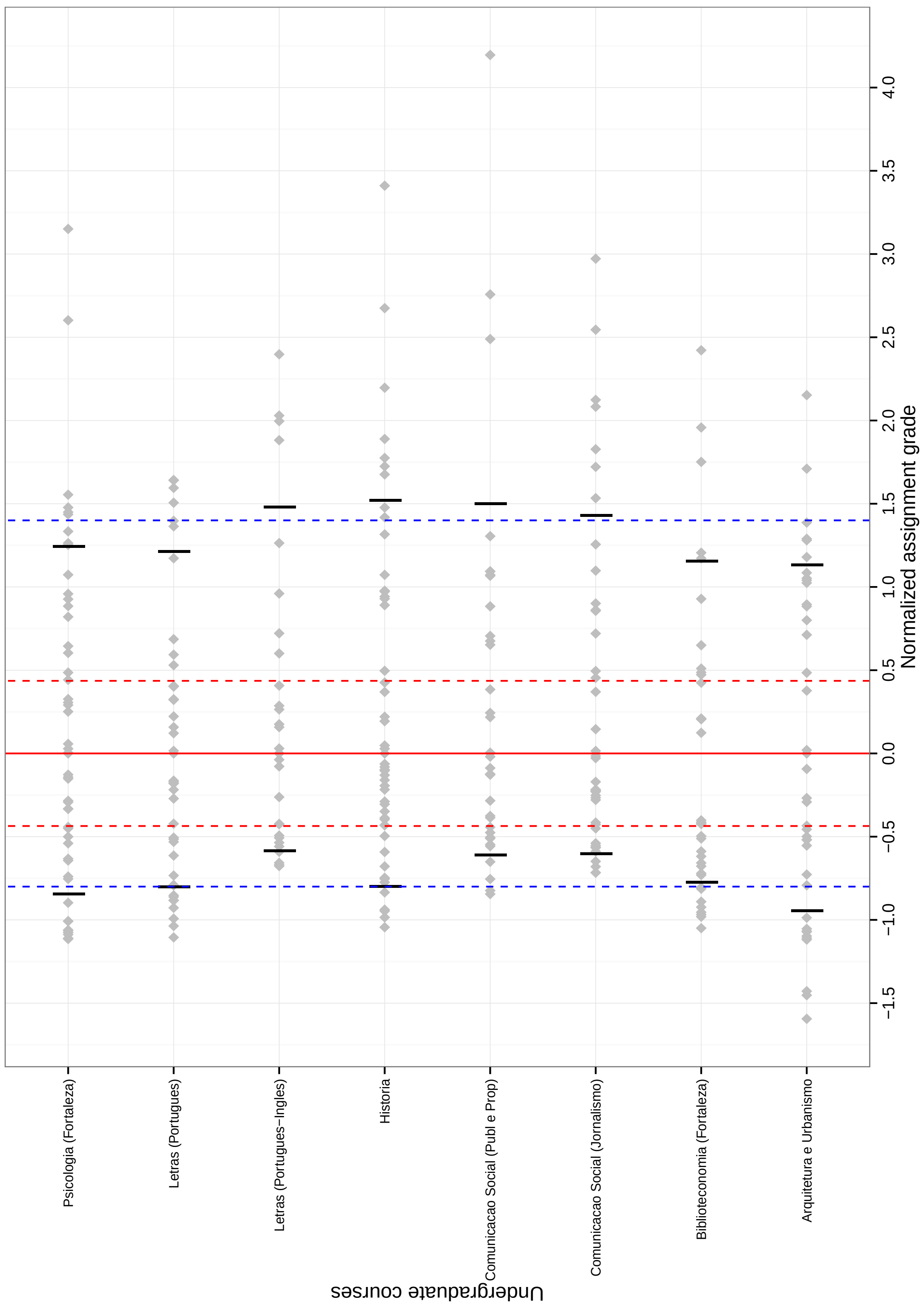
for first semester classes, while this is not the case for courses such as *Economia Domestica* (3) . Another example of this heterogeneity is due to the distribution dispersion. In courses like *Medicina* (1) , the dispersion is very low, with the dots very close to each other, while in *Zootecnia* (3) this

Figure 3: Distribution of normalized assignment grade by courses - College of Sciences and College of Agricultural Sciences



is exactly the opposite. In light of such evidence, we defined four categories or levels of treatment, according to the competition degree in each class, measured by the average SAG. These definitions are given in table 3.

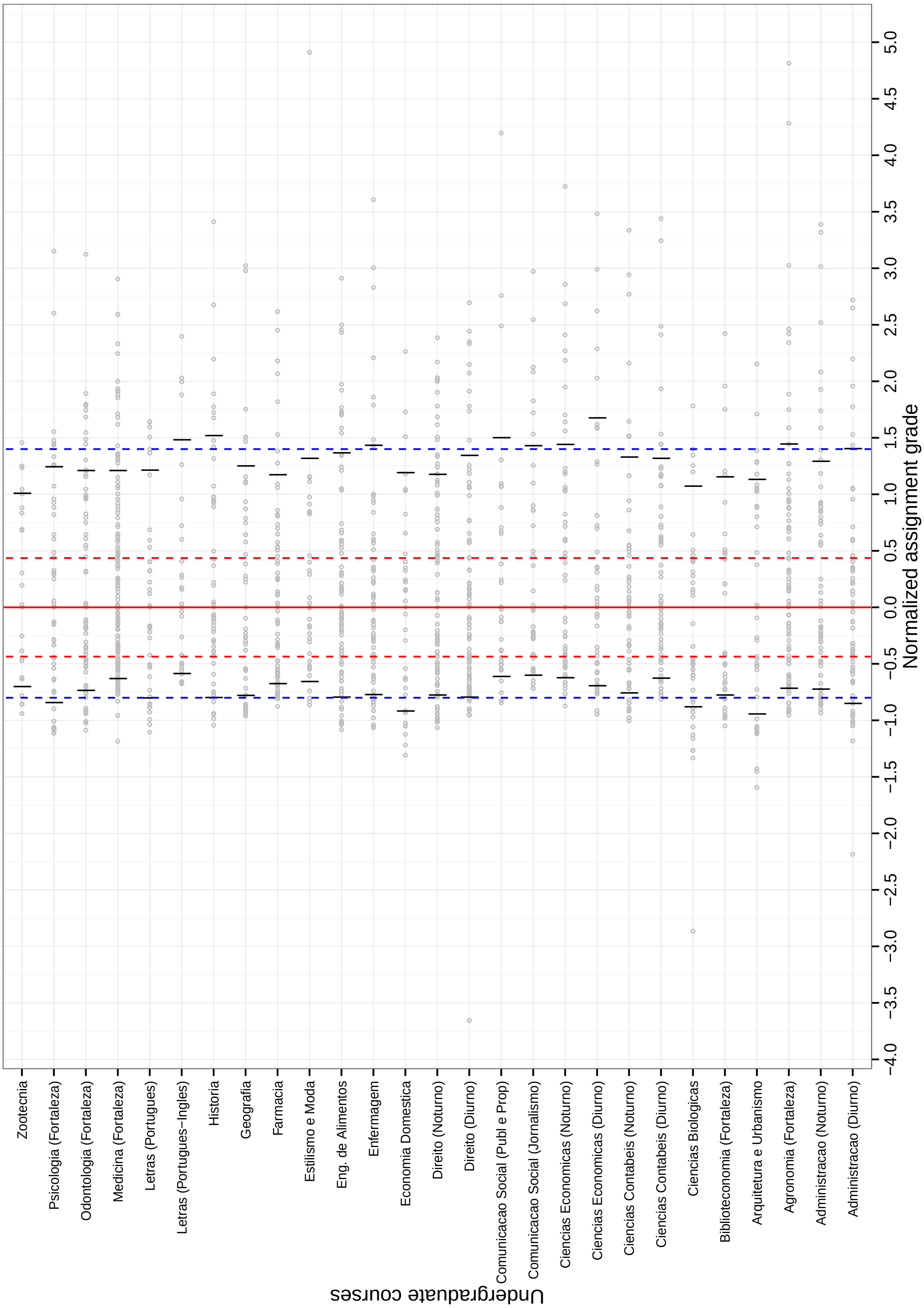
Figure 4: Distribution of normalized assignment grade by courses - College of Humanities



Thus, we defined as high (or low) competition, classes whose average SAG is on the right (or left) of the dashed blue line[5], limited by the solid red line. Each class threshold values were set ***ad hoc***. There are lower and upper bounds of the entire sample, representing the bottom and top 18%,

[5]The dashed red lines define the bandwidth used in the Sharp Regression Discontinuity Design model.

Figure 5: Distribution of normalized assignment grade by courses



respectively. Next section presents the empirical model to analyze the effect of being in the first semester class.

Table 3: Definitions of treatments groups

Group	Control (2^{nd} S)	Treatment (1^{st} S)	Definition
T1	$SAG <$ -0.8	$SAG \in$ [0,1.4]	Courses with lower competition in 2^{nd} S class and lower competition in 1^{st} S class.
T2	$SAG \in$ [-0.8,0)	$SAG \in$ [0,1.4]	Courses with higher competition in 2^{nd} S class and lower competition in 1^{st} S class.
T3	$SAG <$ -0.8	$SAG >$ 1.4	Courses with lower competition in 2^{nd} S class and higher competition in 1^{st} S class.
T4	$SAG \in$ [-0.8,0)	$SAG >$ 1.4	Courses with higher competition in 2^{nd} S class and higher competition in 1^{st} S class.

Source: Elaborated by the authors

5 Empirical strategy

Since the vestibular exam has a sharp design, we can estimate the effects of being in the first semester class on students' academic outcomes by the following model:

$$IRA_{it} = \beta_0 + \beta_1 T_i + \beta_2 SAG_i + \beta_3 T_i SAG_i + \delta X_i + \alpha_k + \alpha_t + \varepsilon_i \quad (2)$$

Where IRA_i is the academic performance index for student i, T_i is a dummy variable indicating whether a student i belongs to the first semester class, SAG_i is the standardized assignment grade, X_i is a student-specific vector of control variables such as age, gender and income. Given that our data set has information for four years (8 semesters), we are able to include fixed effects for courses and time, α_k and α_t, respectively, enabling us to improve our estimators' efficiency. Finally, ε_i is the error term.

This model estimation can be done by means of parametric and nonparametric techniques. For the first case, the exercise must include high-order polynomial for the forcing variable in the model and use data distant from the cutoff. Following a nonparametric estimation, we must choose a window of width h around the cutoff, and use this ***local*** data to perform the estimation.

Gelman and Imbens (2014) present three arguments against the use of high-order polynomials. Firstly, the implicit weights for approximations are not attractive; secondly, the results are sensitive to the polynomial approximation order; lastly, conventional inferences hold poor properties under this setting. Therefore, the authors suggest estimators based on smooth functions such as local linear or quadratic polynomials. So, following this guidance, we estimate our models by means of nonparametric techniques. Specifically, the approach here is a local linear regression.

The local linear regression is a nonparametric way to consistently estimate the treatment effect in a regression discontinuity design (Lee and Lemieux 2009). This method consists in fitting linear regression functions to observations within a distance h on either side of the discontinuity point. Then, treatment effects are given by the difference in intercept estimative for these two equations. Alternatively, one can estimate the average effect directly in a single regression, by solving equation 3 (Imbens and Lemieux 2008):

$$min_{\beta,\delta} = \sum_{i=1}^{N} 1\{c - h \leq SAG_i \leq c + h\}.(Y_i - \beta_0 - \beta_1 T_i - \beta_2 SAG_i - \beta_3 T_i SAG_i - \delta X_i)^2 \quad (3)$$

In this type of model, the researcher faces two important issues: selecting the kind of kernel function to be used, and, more importantly, the bandwidth determination. With respect to the first point, Imbens and Lemieux (2008) advocate that the use of a rectangular kernel, or a more sophisticated version, do not make much difference in the asymptotic bias. In this sense, if there is a difference when one varies the weights of a more sophisticated kernel, it is that the results are highly sensitive to the bandwidth. Hence, the only case in which more sophisticated kernels might be alluring is when the estimates are not much credible due to a high sensitivity in this bandwidth choice.

Even though the arguments presented in Imbens and Lemieux (2008) must be taken seriously, we will proceed with a triangular kernel. This is based on the well-known result that this kernel is an optimal choice for estimating local linear regressions at the boundary (Fan and Gijbels 1996). The triangular kernel function is given by the following expression:

$$K(u) = (1 - |u|) \quad \text{for} |u| \leq 1, \quad \text{where} \quad u = \frac{X_i - X_c}{h} \tag{4}$$

Where X_c is the cutoff point and h is the bandwidth.

The triangular kernel puts more weight, linearly, on observations closer to the cutoff point. So, the difference between regressions using a rectangular or triangular kernel is that the latter involves estimating a weighted regression within a bin of width h, while the former is an unweighted regression (Lee and Lemieux 2009).

The bandwidth determination is more intricate. According to Lee and Lemieux (2009), setting it in a nonparametric structure involves finding an optimal balance between precision and bias. If the researcher uses a larger bandwidth, more observations are available and thus he/she can obtain more precise estimates. However, the linear specification is less likely to be accurate when a larger bandwidth is used, which can bias the treatment effects estimation.

Due to the previously mentioned problems, the bandwidth (h) choice must be made guided by the available data to avoid arbitrary choices, and always taking its trade-off between bias and efficiency into account. To this task, we will follow Imbens and Kalyanaraman (2011)'s algorithm. This algorithm is developed to the bandwidth estimation, focusing on the local linear regression approach. The authors derived an asymptotically optimal bandwidth, conditioned on unknown data distribution functionals, and then proposed simple and consistent estimators for these functionals, obtaining a fully data-driven bandwidth algorithm.

The optimal bandwidth estimator proposed in Imbens and Kalyanaraman (2011) is given by:

$$\hat{h}_{opt} = C_K . \left(\frac{\hat{\sigma}^2_-(c) + \hat{\sigma}^2_+(c)}{\hat{f}(c).((\hat{m}^{(2)}_+(c) - \hat{m}^{(2)}_-(c))^2 + (\hat{r}_+ + \hat{r}_-))} \right)^{1/5} .N^{-1/5} \tag{5}$$

Where the quantities $\hat{\sigma}$, $\hat{m}$, $\hat{f}(c)$ and $\hat{r}$ are, respectively, the conditional variance, conditional mean, the marginal distribution of the forcing variable X at threshold c, and the regularization term. Subscripts $+$ and $-$ are to identify the right or left positioning with respect to the threshold [6].

For the multi-treatment model estimation, we follow this same logic. The only difference here is that we subset our data into four competition levels, and run this model for each different category. With the estimates in hand, we are able to define two measures, commonly used in literature of multi-treatment effects: i) the incremental comparison, in which successive levels of treatment are compared; ii) the control comparison, where the different treatment levels are compared to a reference level (Lee 2005). According to Lee (2005), assuming that the treatment effect at level i is given by μ_i, we have:

- Incremental effect: μ_i - μ_{i-1}, $\forall i$
- Comparison with the control effect: μ_i - μ_0, $\forall i$ When treatment 0 is the control

This is the methodological framework used in this paper. Next section presents the estimation results.

[6] For more details, see the complete work of Imbens and Kalyanaraman (2011).

6 Results

Grounded on the Imbens and Kalyanaraman (2011) algorithm, we obtained a bandwidth of 0.4360537[7]. Table 4 shows the estimation results of model 2 under this value.

Table 4: SRD estimates for the effect of being in the first semester class on students' IRA

Variable	Estimate	Stad. Dev.	t value	p-value
Intercept	8.5577	0.2138	40.0266	0.0000
Tr	-0.1973	0.0533	-3.6990	0.0002
SAG	-0.0411	0.2220	-0.1852	0.8531
Tr*SAG	0.7509	0.3009	2.4952	0.0126
Age	-0.0201	0.0062	-3.2707	0.0011
Gender	-0.2546	0.0345	-7.3877	0.0000
Log(income)	-0.0362	0.0177	-2.0401	0.0414
Bw = 0.4360537	$\bar{R}^2$=0.4474	N=4256	Nl=2376	Nr=1880

Source: Elaborated by the authors

The results presented in table 4 show that, in fact, there is a significant difference in academic performance between students in the first semester class just above the cutoff, and those in the second semester class just below this threshold. In the first case, students have a lower academic performance when compared to those (quite similar in the vestibular results) starting their studies in the second academic semester. The magnitude of this negative effect is about 0.1973, as indicated by the coefficient of variable Tr. This represents a 2% decrease in IRA, since it is measured in a 10-point scale.

In other words, we find that, contrary to what usually happens in peer effects studies for primary and high schools (see, for example Vardardottir (2013) and Foureaux Koppensteiner (2012)), belonging to a group of classmates of top students did not benefit those ranked at the bottom of first semester classes. Actually, it goes on the opposite direction, being harmful to their academic performance, *vis-a-vis* students at the top of second semester classes. Concerning high education, our results are similar to those in Contreras, Badua, and Adrian (2012), which also found negative peer effects, and go against the conclusions in De Paola and Scoppa (2010), Androushchak, Poldin, and Yudkevich (2012) and Booij, Leuven, and Oosterbeek (2015).

For comparison purposes, this is quite similar to the financial aid effect on student's performance, as can be seen in table 5. In their study for Mexican universities, Canton and Blom (2004) obtained an effect equal to 0.174 on a 10-point scale, equivalent to a 2 % improvement in academic performance for students under such financial aid. For the USA, Curs and Harper (2012) studied the same impact on the first-year GPA of students enrolled at University of Oregon. They found values between 0.12 and 0.16 on a 5-point scale, which is equivalent to a GPA improvement ranging from 2.4% to 3.2%.

Now, we turn our attention to the *running variable* SAG and investigate its effect on IRA. Table 4 shows that the SAG coefficient is not significant, suggesting that it does not affect student's academic performance. Nevertheless, note that variable $Tr * SAG$ brings positive and significant results. This indicates that SAG exerts an influence on the academic performance of students in first semester classes, but not in the second semesters counterparts.

The control variables are all significant and exert negative effects on IRA. This means that young male students with a high family income present a lower academic performance than older, female and low income colleagues. The most interesting result here is the fact that high-income

[7] All empirical exercises in this paper were made by means of R Core Team (2014). This bandwidth was estimated using the package "rdrobust" developed by Calonico, Cattaneo, and Titiunik (2015)

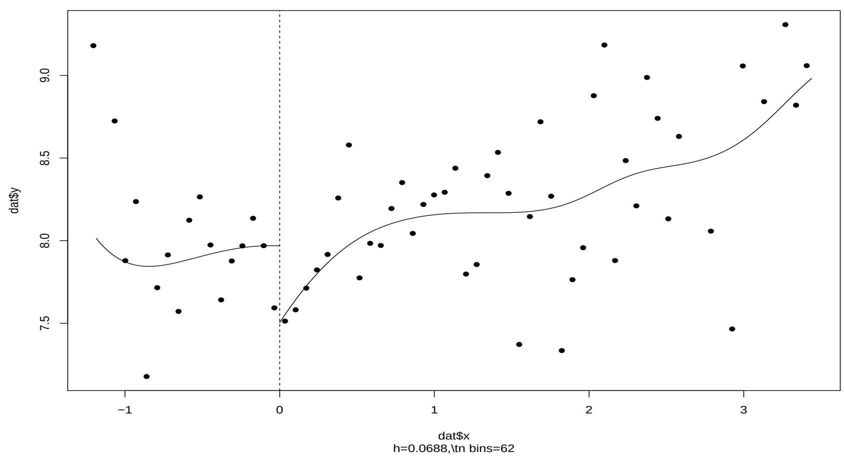
Table 5: Effects of policies in some studies

Authors	Local	Policy	Estimated value (in %)
In this paper	Brazil	Peer effects	2%
Canton and Blom (2004)	Mexico	Financial aid	2%
Curs and Harper (2012)	United states	Financial aid	2.4% - 3.2%

Source: Elaborated by the authors

students have a lower IRA than those of low income. A possible line of explanation is that students from poorer backgrounds, aspiring to change their social status, could invest more efforts to obtain a higher academic performance. Graphically, the results of model 2 are depicted by figure 6.

Figure 6: IRA results as a function of standard assignment grade



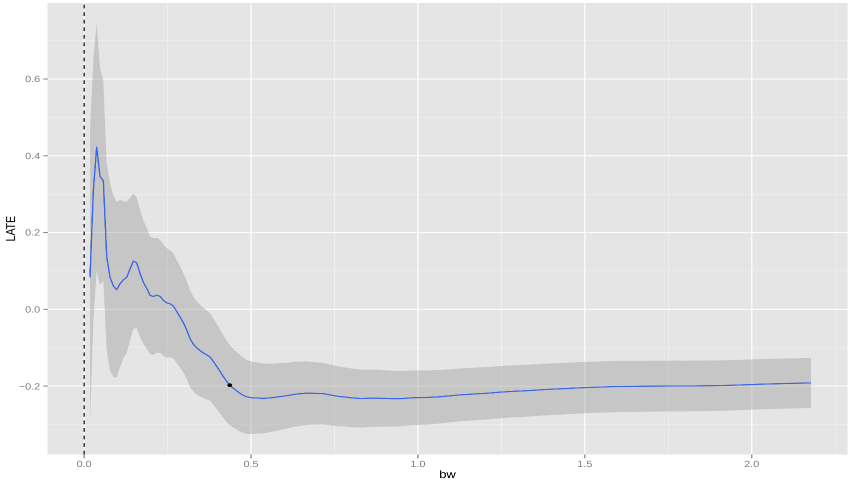
We verified our results' robustness to the bandwidth choice with a regression sensitivity test. This test consists in reestimating model 2 using several bandwidths. After that, we plotted the relation between the bandwidth and the regression discontinuity design's estimates, getting a visually powerful tool to explore the trade-off between bias and precision (Jacob, Zhu, Somers, and Bloom 2012). This is presented in figure 7.

This figure shows the treatment effects' response to a bandwidth variation ranging from 0.01 to 2.18. As expected, for small bandwidth values, precision is low and bias is high, with the treatment effect being positive. As the bandwidth assumes higher values, bias decreases and precision increases, with the treatment effect turning negative. For bandwidths larger than 0.5, the treatment effect is virtually unchanged, indicating that ours results are not much sensitive to the bandwidth choice near this value (remember that the optimal bandwidth is about 0.44).

The next step is to test the assignment variable's continuity around the cutoff. A key assumption in the regression discontinuity design approach is that agents are not able to manipulate the assignment variable. If an individual can manipulate it, then he/she can decide whether or not to receive the treatment, so that continuity assumption may not be plausible. To test the this assignment variable's continuity, we use the McCrary (2008) test.

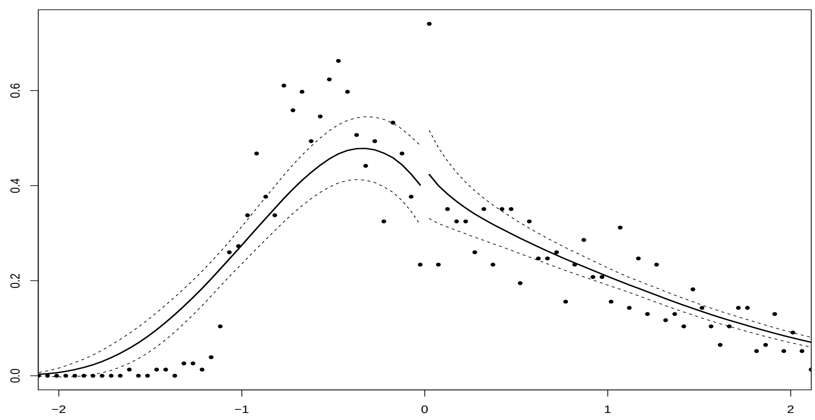
From the McCrary (2008) test, we estimated a discontinuity around 0.10, with $z - value$ and $p - value$ equal to 0.8875 and 0.3748, respectively. In this test, the null hypothesis is that the density is continuous around the cutoff. Given the choosen $p - value$, we cannot reject this null hypothesis,

Figure 7: Sensitivity test



hence our assignment variable is really continuous[8]. The graphical result of this test is shown in figure 8.

Figure 8: McCrary test



Finally, we proceeded with covariates balanced tests. In a regression discontinuity design approach, nothing else, apart from treatment status, is discontinuous in the interval under analysis (Jacob, Zhu, Somers, and Bloom 2012). So, this is equivalent to say that the treatment and control group must be similar. Table 6 presents the test results for equality in both means and distributions of the variables *Age*, *Gender* and $Log(income)$ for first and second semester classes, around the cutoff.

The tests' null hypothesis is that these variables present equal means and distributions around the cutoff. The results shown in table 6 suggest that the only variable with a different mean for each side of the cutoff point is *Age*, since the null hypothesis is rejected (p. value = 0.0186). However, the density test shows that all variables have the same distribution in both cutoff sides. Therefore, grounded by the tests performed, we can conclude that our results are valid, since our data obeys the key assumptions in a regression discontinuity design approach.

[8]This result is not so surprising. Remember that students do not know the cutoff point, since it is determined exogenously by competition. The only information in students' possesion is the number of vacancies. Therefore, we argue that if students do not know the cutoff, then they are not able to manipulate the assignment variable

Table 6: Covariates balanced test

	Mean 2^{nd} S	Mean 1^{th} S	Difference	Statistic	p.value	Density test	p.value
Age	19.5454	18.9276	-0.6178	-2.3614	0.0186	0.1047	0.1127
Gender	0.4579	0.3957	-0.0618	-1.4413	0.1501	0.0622	0.6911
Log(income)	7.4632	7.3417	-0.1215	-1.2732	0.2037	0.0606	0.7212

Source: Elaborated by the authors

Until now, we have analyzed our "global model". Now we turn our attention into the "multi-treatment model". The results are shown in table 7.

Table 7: SRD estimates for the effect of being in the first semester class on students' IRA — Multi-treatment

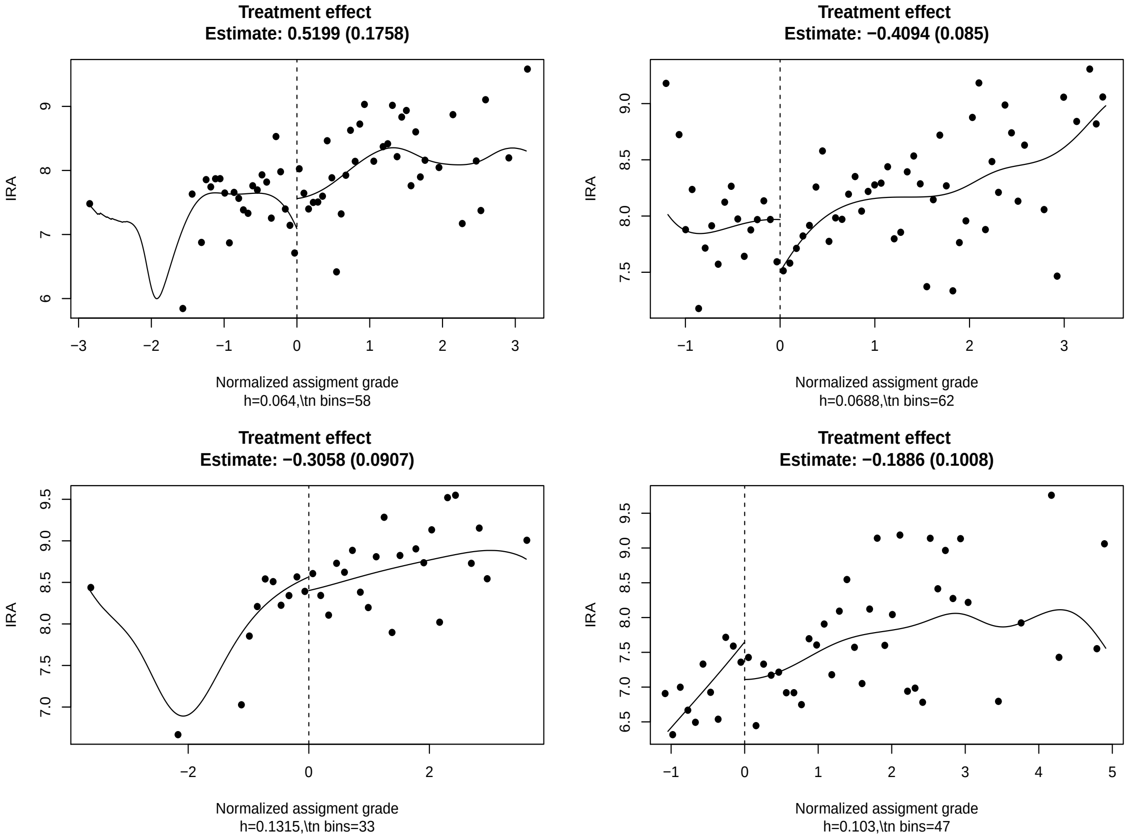
Variable	T1	T2	T3	T4
Intercept	7.8021***	8.2011***	8.9605***	10.3635***
	(0.5267)	(0.3399)	(0.4256)	(0.3725)
Tr	0.5199***	-0.4094***	-0.3058***	-0.1886*
	(0.1758)	(0.085)	(0.0907)	(0.1008)
SAG	-3.9631***	-0.2487	0.5584**	0.8589**
	(1.0568)	(0.4372)	(0.2278)	(0.346)
Tr*SAG	5.6666***	1.0617*	-0.2089	-0.8586*
	(1.2926)	(0.5994)	(0.3178)	(0.5015)
Age	0.0699***	-0.0656***	-0.0086	-0.0758***
	(0.0141)	(0.0121)	(0.0114)	(0.0121)
Gender	0.1081	-0.3346***	-0.3281***	-0.2473***
	(0.1271)	(0.052)	(0.0591)	(0.0666)
Log(income)	-0.1708***	0.0418*	-0.0698*	-0.15***
	(0.0578)	(0.0247)	(0.0375)	(0.0355)
Bandwidth	0.3199	0.3441	0.6574	0.515
$\bar{R}^2$	0.4689	0.3002	0.4131	0.525
N	568	1384	944	1360
Nl	256	800	520	816
Nr	312	584	424	544

Note: Standard error in parentheses
Note: Signif. codes: $p < 0.01$ "***" $p < 0.05$ "**" $p < 0.1$ "*"
Source: Elaborated by the authors

The results demonstrate a statistically significant treatment effect for all groups. It is mentioning that the treatment is positive at the $T1$ level, while in all other levels it is negative. This is just what we found in our "global model". Thus, we can conclude that there are non-linearities in our "peer effects", corroborating the results of Sacerdote (2001) and Zimmerman (2003).

At the $T1$ level, the results indicate that students at the first semester class of courses with low competition in both classes are benefited ***vis-a-vis*** those students in a second semester class. This diference is reflected in an IRA 5% higher for the first students group. Regarding the negative treatment effect levels, $T4$ has a magnitude for the effect quite similar to that found in the global model. However, the effects in levels $T2$ and $T3$ are, respectively, 2 and 1.5 times larger, presenting students in first semester classes with IRA 3% and 4% lower than second semester students. A graphical representation of our results for the multi-treatment model is given by figure 9.

Figure 9: IRA results as a function of assignment grade



Now, we are able to discuss the comparison with the control, as well as to analyze the incremental effects. Both measures are presented in table 8. We begin analyzing the comparison with the control effect, which we defined as being $T1$. The best way to understand this is by thinking about a first-semester student. $T1$ has both classes with low competition and a positive treatment effect. $T2$ has the first semester class associated to a high competition and, thus, the student's loss is 0.9292, compared to $T1$. In $T3$, the first semester class continues to be of low competition, but that of the second semester is a high competition class now. In this case, the students' loss is less than in $T2$. Finally, in $T4$, both classes are of high competition, and the students' loss is 0.7085, i.e., less than in $T2$ and $T3$.

Now, we are going to analyze the treatment's incremental effect following the same logic as previously. The change from $T1$ to $T2$ is already analyzed. When the treatment of a first-semester student is initially $T2$, and changes to $T3$, his/her class becomes of low competition, and high competition is associated with the second semester class. In the case of a change from $T3$ to $T4$, both classes are of high competition now. In both changes, there is no significant effect.

Therefore, we can conclude that the peer effects are positive when both classes are of low competition, and negative in the other cases. However, note that this negative effect is lower when both classes are of high competition. In addition, the incremental effect is significant only when first and second semester classes present high and low competition, respectively.

7 Final Considerations

This paper sought to apply a well-established methodological approach in a new context: the study of peer effects in a Brazilian university. Due to specificities of the entrance process at the

Table 8: Incremental and comparison with the control effects

Statistic	Definition	Value	Std. Dev.	z-value
Comparison with control				
E(T2 - T1)	β_{T2} - β_{T1}	-0.9292**	0.5107	-1.8194
E(T3 - T1)	β_{T3} - β_{T1}	-0.8256*	0.5162	-1.5992
E(T4 - T1)	β_{T4} - β_{T1}	-0.7085*	0.5259	-1.3470
Incremental				
E(T2 - T1)	β_{T2} - β_{T1}	-0.9292**	0.5107	-1.8194
E(T3 - T2)	β_{T3} - β_{T2}	0.1035	0.4192	0.2470
E(T4 - T3)	β_{T4} - β_{T3}	0.1171	0.4376	0.2676

Note: Signif. codes: $p < 0.01$ "***" $p < 0.05$ "**" $p < 0.1$ "*"
Source: Elaborated by the authors

Federal University of Ceará until 2010 — the so called vestibular exam — we are able to use the methodological tools provided by the regression discontinuity design approach, more specifically its sharp version, to estimate peers effects among higher education students.

From this sharp regression discontinuity design approach, we estimated the effect of being in first ***versus*** second semester classes. We found that, in contrast to what usually happens in studies of peer effects in primary and high schools, being a classmate of high-ability students, i.e. being part of a first semester class, is harmful to a typical student. We obtained a negative effect of about 0.1973, indicating that these students have an academic performance 2% lower than those of second semester classes. For the sake of comparison, this effect is quite similar to what Canton and Blom (2004) and Curs and Harper (2012) obtained in a financial aid context.

Taking advantage that, in our data set, the undergraduate programs have heterogeneous patterns in assignment grades distributions, we classified these programs in four categories, according to the competition in first and second semester classes. After this, we estimated a model capable to assessment a multi treatment. We found, as in Sacerdote (2001) and Zimmerman (2003), that the peer effects present non-linearities. In cases which both classes are of low competition, the peer effects are positive, presenting students of first semester classes with an IRA 5% higher, while in case both classes are of high competition, these students have an IRA 2% lower.

As suggestions for future studies, we believe that the development of a model for the new entrance process by means of SISU could be made. We also believe that replicating our empirical exercise on different data sets, coming from different institutional backgrounds, might be something worth pursuing to validate our approach. Finally, we believe that this should be done with ENADE's [9]score as an outcome, instead of $IRA's$. It would help us to understand this effect better.

References

Abdulkadiroğlu, A., J. Angrist, and P. Pathak (2014): "The elite illusion: Achievement effects at boston and new york exam schools," ***Econometrica***, 82(1), 137–196.

[9]The National Survey of Students' Performance (ENADE) is an exam that constitutes the National System of Higher Education Assessment (Sinaes). This test aims to assess students' performance in relation to the syllabus provided in the curriculum guidelines of their undergraduate programs, and the skills and competences in their training (de Estudos e Pesquisas Educacionais Anísio Teixeira (Inep) 2015).

ABREU, L. C. M. (2013): “Mecanismos de seleÃ§Ã£o Gale-Shapley dinÃ¢micos em universidades Brasileiras: $SISU$, $SISU_{alpha}$, $SISU_{beta}$,” DissertaÃ§Ã£o de mestrado, Universidade Federal do CearÃ¡.

ANDROUSHCHAK, G. V., O. POLDIN, AND M. YUDKEVICH (2012): “Peer effects in exogenously formed university student groups,” WORKING PAPER 03/EDU/2012, National Research University Higher School of Economics.

BOOIJ, A., E. LEUVEN, AND H. OOSTERBEEK (2015): “Ability peer effects in university: Evidence from a randomized experiment,” Discussion Paper 8769, IZA.

BUTCHER, K. F., P. J. MCEWAN, AND C. H. TAYLOR (2010): “The effects of quantitative skills training on college outcomes and peers,” *Economics of Education Review*, 29(2), 187–199.

CALONICO, S., M. D. CATTANEO, AND R. TITIUNIK (2015): *rdrobust: Robust Data-Driven Statistical Inference in Regression-Discontinuity Designs*R package version 0.80.

CANTON, E., AND A. BLOM (2004): *Do student loans improve accessibility to higher education and student performance*. CPB Netherlands Bureau for Economic Policy Analysis The Hague.

CARD, D., AND L. GIULIANO (2015): “Can tracking raise the test scores of high-Abilitybility minority students?,” .

CARRELL, S. E., R. L. FULLERTON, AND J. E. WEST (2008): “Does your cohort matter? Measuring peer effects in college achievement,” Discussion paper, National Bureau of Economic Research.

CARVALHO, J.-R., T. MAGNAC, AND Q. XIONG (2014): “College Choice Allocation Mechanisms: Structural Estimates and Counterfactuals,” Working paper TSE-506, Toulouse School of Economics.

COLEMAN, J. S., E. Q. CAMPBELL, C. J. HOBSON, J. MCPARTLAND, A. M. MOOD, F. D. WEINFELD, AND R. YORK (1966): “Equality of educational opportunity,” *Washington, dc*, pp. 1066–5684.

CONTRERAS, S., F. BADUA, AND M. ADRIAN (2012): “Peer effects on undergraduate business student performance,” *International Review of Economic Education*, 11(1), 57–66.

CURS, B. R., AND C. E. HARPER (2012): “Financial aid and first-year collegiate GPA: A regression discontinuity approach,” *The Review of Higher Education*, 35(4), 627–649.

DE ESTUDOS E PESQUISAS EDUCACIONAIS ANÍSIO TEIXEIRA (INEP), I. (2014): “Censo da educação superior 2013,” .

——— (2015): “Exame Nacional de Desempenho de Estudantes - ENADE,” .

DE PAOLA, M., AND V. SCOPPA (2010): “Peer group effects on the academic performance of Italian students,” *Applied Economics*, 42(17), 2203–2215.

EPPLE, D., AND R. ROMANO (2011): “Peer effects in education: A survey of the theory and evidence,” *Handbook of social economics*, 1(11), 1053–1163.

FAN, J., AND I. GIJBELS (1996): *Local polynomial modelling and its applications: Monographs on statistics and applied probability 66*, Chapman & Hall/CRC Monographs on Statistics & Applied Probability. Taylor & Francis.

FOUREAUX KOPPENSTEINER, M. (2012): “Class assignment and peer group effects: Evidence from Brazilian primary schools,” Discussion paper, Department of Economics, University of Leicester.

GAWANDE, A. (n.d): "BrainyQuote.com," `http://www.brainyquote.com/quotes/quotes/a/atulgawand527239.html`, Accessed: May 22, 2015.

GELMAN, A., AND G. IMBENS (2014): "Why high-order polynomials should not be used in regression discontinuity designs," Discussion paper, National Bureau of Economic Research.

IMBENS, G., AND K. KALYANARAMAN (2011): "Optimal bandwidth choice for the regression discontinuity estimator," *The Review of Economic Studies*, 79(3), 933–959.

IMBENS, G. W., AND T. LEMIEUX (2008): "Regression discontinuity designs: A guide to practice," *Journal of econometrics*, 142(2), 615–635.

JACOB, R. T., P. ZHU, M.-A. SOMERS, AND H. S. BLOOM (2012): *A practical guide to regression discontinuity*. MDRC.

LEE, D. S., AND T. LEMIEUX (2009): "Regression discontinuity designs in economics," Discussion paper, National Bureau of Economic Research.

LEE, M.-J. (2005): *Micro-econometrics for policy, program, and treatment effects*. Oxford University Press Oxford.

LEEDS, D. M., AND S. L. DESJARDINS (2014): "The effect of merit aid on enrollment: A regression discontinuity analysis of Iowa's national scholars award," *Research in Higher Education*, pp. 1–25.

MANSKI, C. F. (1993): "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 60(3), 531–542.

MCCRARY, J. (2008): "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, 142(2), 698–714.

MCEWAN, P. J., AND K. A. SODERBERG (2006): "Roommate effects on grades: Evidence from first-year housing assignments," *Research in Higher Education*, 47(3), 347–370.

MEALLI, F., AND C. RAMPICHINI (2012): "Evaluating the effects of university grants by using regression discontinuity designs," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 175(3), 775–798.

MOSS, B. G., AND W. H. YEATON (2006): "Shaping policies related to developmental education: An evaluation using the regression-discontinuity design," *Educational Evaluation and Policy Analysis*, 28(3), 215–229.

R CORE TEAM (2014): *R: A Language and Environment for Statistical Computing*R Foundation for Statistical Computing, Vienna, Austria.

SACERDOTE, B. (2001): "Peer Effects with Random Assignment: Results for Dartmouth Roommates," *The Quarterly Journal of Economics*, 116(2), 681–704.

SACERDOTE, B. (2011): "Peer effects in education: How might they work, how big are they and how much do we know thus far?," *Handbook of the Economics of Education*, 3, 249–277.

SCHÖER, V., AND D. SHEPHERD (2013): "Compulsory tutorial programmes and performance in undergraduate microeconomics: A regression discontinuity design," Discussion Paper 49716, MPRA.

SILVA, J. E. M. D. (2007): "Vestibular na UFC: ImplicaÃ§Ã$\mu esparaoensinom\tilde{A}©dio - - - Umestudodecasoapartirdasmudan\tilde{A}§asrealizadasde1978a2004,'' Disserta\tilde{A}§\tilde{A}£odemestrado, Universida$

UNIVERSITY, C. F. (2014): "UFC statistical yearbook - A brief edition 2013-2014," .

VAN DER KLAAUW, W. (2002): "Estimating the effect of financial aid offers on college enrollment: A regression discontinuity approach," *International Economic Review*, 43(4), 1249–1287.

VARDARDOTTIR, A. (2013): "Peer effects and academic achievement: A regression discontinuity approach," *Economics of Education Review*, 36, 108–121.

WINSTON, G., AND D. ZIMMERMAN (2004): "Peer effects in higher education," in *College choices: The economics of where to go, when to go, and how to pay for it*, pp. 395–424. University of Chicago Press.

ZIMMERMAN, D. J. (2003): "Peer effects in academic outcomes: Evidence from a natural experiment," *Review of Economics and Statistics*, 85(1), 9–23.