Peer effects in college: how peers' performance can influence students' academic outcomes

Laetícia Rodrigues de Souza
Cristine Campos de Xavier Pinto
Dimitri de Oliveira e Silva
Bernardo Lanza Queiroz

Abstract

There is a large and growing literature on peer effects as researchers have long begun investigating the role of social interactions for explaining a series of individual behaviors. Schools are very important environments for studying peer effects. A sizable portion of human capital accumulation takes place in schools and this has consequences for individual productivity and wages, for instance. This paper is part of a project that investigates the existence of peer effects in academic outcomes (such as grade point average (GPA), grade in mandatory courses, obtained credits, dropout and retention rates) in a developing country. It does so by exploring specificities in the student's admission process of a Brazilian federal university, which works as a natural experiment. Individuals who are comparable in terms of previous academic achievement - based in their score in the admission exam - end up having classmates with better or worse performance in college because of the assignment rule of students to classrooms starting classes either in the first or in the second semester. Thus, our identification strategy for estimating peer effects on academic outcomes eliminates the endogenous self-selection into groups that would otherwise undermine the causal inference of peer effects.

1 Introduction and Justification

There is a large and growing literature on peer effects as researchers have long begun investigating the role of social interactions for explaining a series of individual behaviors. Peer influences may occur in different stages of the life cycle and in different environments. Some studies examine whether workers' productivity increases when they work alongside more productive coworkers (Cornelissen et al., 2017; Mas and Moretti, 2009). Other researchers are interested in investigating peer effects on health outcomes and risky behaviors of children, adolescents and youth, with examples ranging from the influence of peers on an individual's weight gain (Yakusheva et al., 2014; Trogdon et al., 2008) or on an individual's fast food consumption (Fortin and Yazbeck, 2015) to the influence of peers on smoking, drinking, gambling, misbehavior, etc. (Eisenberg et al., 2014; Carrell and Hoekstra, 2010; Gaviria and Raphael, 2001). Peer effects are present in a wide range of individual decisions and choices. For instance, there are studies analyzing how consumption decisions of individuals depend on information they receive from peers (Moretti, 2011), how peer's political identification and/or engagement affects individual political behaviors (Campos et al., 2015), and how peer groups influence the take-up of government social programs (Dahl et al., 2014).

Peer effects can also have important long lasting effects. Analyzing the role of peer social networks in explaining smoking behavior among adolescents who were schoolmates, Ali and Dwyer (2009) found that besides being important determinants of adolescents' smoking behavior, these peer effects persist into adulthood. Chetty et al. (2011) analyze the effect on adulthood of interactions that occurred in childhood in an educational environment as well. Seeking to understand how an individual's kindergarten classroom may affect their earnings in adulthood (among other outcomes), they found that students randomly assigned to higher quality classrooms - measured by students with higher end-of-class test scores - have higher earnings when adults.

Schools are very important environments for studying peer effects. This is so because since kindergarten age, most of individuals may spend half of their day in classrooms frequently surrounded by more than a dozen other individuals. Additionally, a sizable portion of human capital accumulation takes place in schools and this has consequences for individual productivity and wages. These are reasons why most of the researches about peer effects (on the most diverse subjects such as wages, health outcomes, risky behaviors, political engagement, school performance and dropping-out, etc) are based on information on different educational environments (Chetty et al., 2011; Trogdon et al., 2008; Carrell and Hoekstra, 2010; DeLay et al. 2016; Gaviria and Raphael, 2001; Eisenberg et al., 2014; Fortin and Yazbeck, 2015; Campos et al., 2015; Neidell and Waldfogel, 2010).

There is also strong evidence of peer effects on indicators related to educational performance and this is observed at every school level, from pre-kindergarten to college education. Neidell and Waldfogel (2010) verified robust effects of the quality of peers (based on students' test scores) in early education - kindergarten and early elementary grade - on math and reading outcomes among children in the United States. Analogously, De Melo (2014) provided evidence of positive effects of the performance of peers in reading and mathematics scores and mixed evidence on science in her study of Uruguayan primary schools. Using data from Florida elementary public schools, Burke and Sass (2013) found that students with low initial achievement levels appear to benefit less from an increase in the average ability of their peer group than do those with higher initial scores. Many studies of peer effects in college rely on roommates and dormmates since these are often the peer groups which can be easily identified (Sacerdote, 2011). Zimmerman (2003), Sacerdote (2001) and Carrel et al. (2009) found that roommates’ background (such as High School class rank or grade point average - GPA) and current achievement (measured by college GPA) affect own achievement.

The question of whether classroom peer interactions matter for students learning has long been of concern to social scientists, educators, and policymakers. Why peer effects has attracted so much attention? Peer groups effects have played an outstanding role in numerous policy debates (Hanushek et al., 2003). According to Soetevent (2006), this is so because in general policymakers aim at implementing a social policy that ultimately maximizes the welfare of the worst-off individuals. For achieving this goal it is necessary a thorough understanding of the determinants of the decision making process that takes place at the individual level. Neglecting social interaction effects that impact individual decisions is inefficient and may lead to undesirable outcomes and to a reconsideration of the costs and benefits of public policies and initiatives.

Nowadays, many countries are implementing desegregation programs. As social interactions probably influence academic decisions, study habits, and individual aspirations, socioeconomic stratification in the establishment of social networks has important implications for the persistence of educational disparities (Soetevent, 2006; Graham, 2011; De Melo, 2014).The Right to Education Act is an India's nationwide program launched in 2009 which requires that at least 25 per cent of private schools sits are assigned to disadvantaged children (Mehrotra, 2012; De Melo, 2014). In Brazil, public college education began to be influenced by affirmative action policies, with a strong expansion of these policies by 2012 when it was established that 50 per cent of seats in Federal universities in the country should be assigned to disadvantage students (Rossetto and Gonçalves, 2015).

Graham (2011) emphasizes that an effective policy-making requires knowledge of the causal mapping from group composition into outcomes. Any meaningful educational program would generate large changes in the allocation of students, and hence peer groups, across schools/universities. The magnitude and structure of any peer group effect in learning would be a key determinant of these changes. It would also determine their effects on the level and distribution of student achievement. For these reasons knowledge of any peer spillover is required for optimal educational program design.

In spite of the relevance of the subject, according to Hanushek et al. (2003), only few direct investigations of the effect of peer groups on student performance had been done up to the beginning of 2000s. Soetevent (2006) surveyed the extent to which recent empirical contributions have succeeded in overcoming the challenges in truly estimating the effects of peers academic performance on students achievements in university. The author analyzes eight prominent studies published before mid-2000s. All of them are in American universities. In fact, research exploring peer effects on student achievement using developing countries data is extremely scarce (Asadullah and Chaudhury, 2008; Soetevent, 2006).

Much debate has addressed the actual relevance of peer effects especially given the identification challenges posed by any study of social interactions (De Melo, 2014). Peer effects on student performance may have important implications for designing college courses. On one hand, if there are no peer effects, grouping students by levels of ability is desirable since teachers can adjust resources/classes according to each class' skills. On the other hand, if there are positive peer effects, mixing poor-performing students with better ones may be more efficient as long as this does not harm the latter (Chen et al., 2015). However, peer effects are notoriously difficult to estimate econometrically because in most contexts people choose with whom they associate. Therefore, while similarities in behavior among members within the same group may be due to peer effects, it is difficult to rule out the possibility that group members may be similar to each other along unobserved dimensions or may have come together with the intention of achieving similar outcomes (Kremer and Levy, 2008).

Using a unique dataset on students in one of the flagship universities in Brazil, we are able to deal with the identification challenges that plague the extant literature. This paper proposes to investigate the existence of peer effects in academic outcomes (such as grade point average (GPA), grade in mandatory courses, obtained credits, dropout and retention rates) in a developing country. It does so by exploring specificities in the Federal University of Minas Gerais (UFMG) selection process. In particular, there is only one entrance exam per year[1], but based on this exam, two classes of students are formed: one group begins the course in the first semester while the other begins in the second semester of each year. Roughly speaking, students who were admitted to the university are ranked according to their entrance exam score and the half portion with the best scores enter in the first semester, while the others enter in the second semester. This assignment rule causes some individuals who scored similarly in the entrance exam to have peers of very different quality in terms of previous achievement. Indeed, the worse ranked among those who entered in the first semester usually have a similar score to the individuals best ranked among those who entered in the second semester, but the former have peers all scoring better than the peers of the latter. Hence, by comparing academic outcomes of individuals who were at the margin of being assigned to different semesters we can estimate the extent of peer effects. Technically, the discontinuous assignment rule allows a causal inference of peer effects based on a regression discontinuity approach (Imbens and Lemieux, 2008; Lee and Lemieux, 2010, 2015).

There are some studies on the determinants of educational performance in Brazil and, in particular, related to the effects of peers in the context of different school levels, with the latest ones focusing in university environments: André (2016), Poldin et al. (2015) and Matta et al. (2016). These studies found opposite peer effects on achievement and as far as we know, these are the only studies intended to estimate peer effects on academic achievements in Brazilian universities. They were all publicized (only one of them was actually published in a journal) in the last year, reinforcing the importance and contemporaneity of this research object.

[1]Since the 1970s, when UFMG began to organize its admission exams, UFMG always had a single selection process per year to fill two classes of students - one beginning in the first semester and another beginning in the second. This decision was mainly related to logistics, as organizing the admission exam is an extremely complex task. The only exceptions in this historical series from 1970 to 2017 are the years 2014 and 2015, in which there was two annual *Vestibular* editions.

Studies such as the one we are proposing here can help clarifying some fundamental points to be considered for instance when designing educational policies and, therefore, are of interest not only to school administrators, but also to parents, students and the whole society.

2 Methodology

Studying the influence of peers on students' academic achievements has attracted considerable interest as it enhances our understanding of the educational process. However, measuring peer effects is a difficult task. This is so because students' outcomes depend on numerous factors and isolating peer influences is particularly problematic since people typically choose those with whom they associate (Zimmerman, 2003).

We overcome these identification problems by using a unique Brazilian federal university dataset[2].

2.1 The data

We will use a rich set of administrative data from the Federal University of Minas Gerais (UFMG). Founded in 1927, UFMG is one of the best Brazilian higher education institutions. Based on indicators of research, innovation, internationalization, teaching and job market insertion, UFMG was classified as the fourth best university in the country (RUF 2016) and the seventh best university of America Latina (THE 2016).

Being free of charge and holding a high quality status compared to their private counterpart, federal universities generally attract students from a wide range of socioeconomic backgrounds, and this makes the competition for a seat very fierce. In this context, UFMG is also one of Brazil's largest universities with more than 3,100 teachers and nearly 32,000 students enrolled in 90 undergraduate courses in 2015 (MEC and INEP, 2016).

Although UFMG students' data is not publicly available and getting access to it took a while, we have now access to their datasets and are working on cleaning, organizing and consolidating it.

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[2] André (2016) also estimated peer effects on college academic performance of students of the Federal University of Ceará (UFC) using an equivalent natural experiment. However, the similarities of this proposal with the purpose of his dissertation end here. This proposal goes further while estimating peer effects on college academic achievement mainly by: 1) analyzing additional academics outcomes (in addition to the GPA), such as grade in mandatory courses, obtained credits, dropout and retention rates and 2) the use of a significantly longer period, between 2005 and 2013 (in comparison to year 2008) with the possibility of controlling for teachers' fixed effects which is advised by other studies (Burke and Sass, 2013; Duflo et al., 2011). As additional points, it is worth mentioning that we will use information on students from a university located at the Southeast region, the most developed region of the country (in comparison to an university in the least developed region, the Northeast) and which is one of the best universities of Brazil and Latin America (according to Ranking Universitário Folha and THE World University Rankings, UFMG is among the top 5 (top 10) universities in Brazil (Latin America).

In general, there is information on student entrance exam scores, information on the admission course, the year and semester that each student entered, besides having information on students' academic situation (regular, drop-out, conclusion), GPAs, Brazilian State of origin, marital status, race, sex, reason why choosing the course, how many times the student tried to get into a university before and a series of demographic and socioeconomic variables such as whether the student studied at public schools, is working or has ever had a job, mother and/or father is alive, mother's and father's education and occupation, monthly family income, household assets, among others. Additionally, we got information about the grade in mandatory courses, obtained credits, grade retention, the student's classes and disciplines. Also, we got access to the candidate's handbook and the college admission exam (which in Brazil is called *Vestibular*[3]) resolution regarding the whole period of years of this study.

We managed to get access to data with this information spanning the years 1995-2013[4]. Our population is composed of more than 77,000 UFMG students. Table 1 shows some general descriptive statistics for years 1995, 2005 and 2013, respectively the beginning, middle and the end of the period of the data we are working on.

[3]Traditionally, UFMG admission process was divided in two stages. The first stage comprised 8 tests with multiple choice questions related to subjects in the core of High School (Biology, Physics, Geography, History, Foreign Language (Spanish, French or English), Portuguese Language and Brazilian Literature, Mathematics and Chemistry). The second stage consisted of a writing test, common to all courses, and of specific tests by course. Since 2011 the ENEM (National High School Exam) was adopted as the first stage of UFMG entrance exams and in 2014 the ENEM was adopted as the only admission exam and the second stage was no longer applied.

[4]As explained in footnote 1, exceptionally in 2014 and 2015, UFMG had two admission exams instead of one as it used to be in all previous years. This is the reason why the most recent year we are going to use in our analysis is 2013.

UFMG Students in 1995, 2005 and 2013 according to Selected Characteristics

Variables	Percentage of students		
	1995	2005	2013
Admission course area			
Agrarian and Biological Sciences	6.74	7.39	6.63
Exact and Earth Sciences	11.75	12.39	11.63
Humanities	13.73	12.39	12.18
Applied Social Sciences	20.3	20.02	18.77
Engineering	14.62	16.52	17.14
Linguistics, Letters and Arts	9.44	9.69	12.45
Health	23.42	21.6	21.2
Classes were taken during the day	89.06	79.34	65.71
Admission was in the first semester of the year	53.86	54.61	57.57
Female	47.51	47.15	55.83
Studied High School in Public School (in whole or in part)	39.05	37.3	44.28
Work			
Worked up to 20 hours per week	7.17	9.63	6.71
Worked more than 20 hours per week	23.63	15.27	19.59
Did not work	69.2	75.1	73.7
Monthly Family Income (in Min. Wages)			
Up to 2	2.59	5.53	13.42
From 2 to 5	14.61	22.57	35.96
From 5 to 10	22.85	26.73	23.57
More than 10	59.95	45.18	27.05
Number of people living on family income			
One	2.59	1.89	2.72
2 or 3	21.45	23.73	32.67
4 or 5	55.22	64.06	58.18
5 or 6	17.06	9.31	5.91
6 or more	3.68	1.01	0.51
Paternal education			
Did not complete Elementary School	22.59	18.55	16.53
Completed Elementary School	12.34	10.71	11.32
Completed High School	22.82	27.35	31.79
Completed College	42.25	43.38	40.36
Maternal education			
Did not complete Elementary School	22.32	15.52	12.98
Completed Elementary School	13.6	9.06	9.29
Completed High School	33.64	33.69	32.41
Completed College	30.44	41.72	45.31
Variables	**Average**		
	1995	**2005**	**2013**
Entrance exam score (Vestibular)	211.49	184.59	152.02
GPA			
First semester	3.02	3.35	2.94
Second semester	3.04	3.27	2.73
Third semester	3.05	3.15	2.73
Fourth semester	3.25	3.25	2.81
Age	21.22	21.06	21.38
Total number of students	3591	4666	6618

2.2 Empirical strategy

Rules for admission to UFMG establishes that each candidate can choose, according the preferences, up to two courses among the ones available at the university before taking the entrance exam. Then, based on the ranked preferences and grades of all candidates, each candidate is informed whether they were classified to enroll in their first choice of course, in their second choice, or whether they were not classified to enroll in any of them. This way, at the end of the process, all candidates are ranked by their grades in the entrance exam and this ranking determines the ones who were admitted to the university and those who were not (based on the number of seats available). Finally, university seats are filled according to the candidates' admission exam grades. Generally, from the students admitted to a course, half of them with the best scores are assigned to the class entering in the first semester and the other half is assigned to the class entering in the second semester. This is usually done for every course. This feature on the assignment of the admitted candidates - allocating students to first or second semesters based on their grades - allows us to employ a Regression Discontinuity Design (RDD) approach to analyze peer effects among students in a Brazilian federal university environment.

The RDD offer a way of estimating treatment effects in a non-experimental setting where treatment is determined by whether an observed assignment variable exceeds a known cutoff point (Lee and Lemieux, 2010, 2015; Imbens and Lemieux, 2008). This is the case of the analysis we propose in this paper. We intend to analyze the effects of peers on academic outcomes, using the fact that the allocation of the students to classes was based on an observed entrance exam score. The main idea behind the RDD is that students with grades just above the cutoff (the ones assigned to enter in the first semester) are good comparisons to those just below the cutoff (who were allocated to the second semester). This way, the difference between the academic performance of both groups of students will be driven by the fact that the ones in the first semester are surrounded by "better peers" - in terms of previous academic performance - in comparison to the ones assigned to the second semester.

According to RDD approach, assignment to treatment is determined, either completely or partly, by the value of a predictor being on either side of a fixed threshold. Settings where treatment is only partially determined by whether the assignment variable crosses a cutoff point - as for example in cases of imperfect take-up by program participants or when factors other than the threshold rule affect the probability of program participation - are referred to as "fuzzy" RDD (Lee and Lemieux, 2015). The case of this paper is initially treated as a "sharp" RDD[5] as the

[5]We say, that "we initially use a sharp RDD approach" because whether individuals choose not to enroll in university once they get the result of the class that they were assigned to, the RDD becomes fuzzy, as in that case there will be an imperfect take-up. Hence, after further investigating the UFMG admission process and the data we will have access to, we may need to resort to a fuzzy RDD approach.

assignment to treatment is determined by crossing a cutoff point since students above a certain grade in *Vestibular* will be allocated to the first semester while the remaining will start classes later. In this case, the probability of treatment (being allocated to the first semester) jumps from 0 to 1 when the assignment variable (the *Vestibular* score) crosses the threshold (the minimum grade that fill the maximum number of students of a class/course).

This students' allocation scheme into classes is crucial for our analysis of peer effects on academic outcomes as having prior information specifying the composition of reference groups is the only way of making feasible inferences on this causality. According to Manski (1993), inferring on peer effects is difficult because there are three hypotheses explaining the fact that individuals belonging to the same group tend to behave similarly: 1) endogenous effects - the propensity of an individual to behave in some way varies with the behavior of the group; 2) exogenous (contextual) effects - the propensity of an individual to behave in some way varies with exogenous characteristics of the group, and 3) correlated effects - individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments. To make it clearer how these hypotheses work, consider our analysis of students' college achievement as an example. All else equal, there is an endogenous effect if individual achievement tends to vary with the average achievement of their classmates. There is an exogenous effect if, for instance, achievement tends to vary with the socio-economic composition of the students in the class. Finally, there are correlated effects if students in the same class tend to have a similar achievement because they have similar backgrounds or because they have the same teachers.

Our identification strategy for estimating peer effects on academic outcomes eliminates the endogenous self-selection into groups that would otherwise undermine the causal inference of peer effects. Since RDD is "as good as a randomized experiment", students with grades on either side of the threshold - which defines who enters in first semester, and thus get higher quality peers, and who enters in the second semester, and thus get lower quality peers - are very similar to each other in every relevant respect except for the fact that some are surrounded by better peers while others are not. This way, peer effects can be computed by comparing the average of post-admission outcomes of individuals within a small bandwidth around the rank that determined whether they are assigned to one class or another (Lee and Lemieux, 2010). It is worth highlighting the fact that we are interested in different academic performance measures such as dropout and retention situation, obtained credits, GPA and grade in mandatory courses.

Also, we seek to control for possible correlated effects. We intend to include teacher fixed effects in our estimation of peer effects. However, the inclusion of this information depends on the data that will be made available to us. It is also possible that at least for most of UFMG admission years, students selected to both the first and the second semesters are taught by the same teachers; if this is the case, our estimates will already be taking it into account.

Angrist and Pischke (2008) formally describes the RDD approach as follows.

Sharp RDD is used when treatment status, D_i, is a discontinuous function of a covariate, x_i. For illustration, assume there is only one course in the university. The covariate x_i is given by $x_i = ½ - r_i/s$, where r_i is the rank of the admitted student i and s is the number of available seats for the course chosen by the student. The variable D_i is then given by

$$D_i = \begin{cases} 1 \; if \; x_i \geq x_0 \\ \\ 0 \; if \; x_i \leq x_0 \end{cases} \qquad Equation\ 1$$

In our analysis, $x_0$is the normalized cutoff rank, which equals to zero here[6]. It is a discontinuous function because no matter how close a student's grade $x_i$gets to the cutoffx_0, the student's allocation is unchanged until $x_i = x_0$.

Let Y_i be a post-admission academic outcome of interest. In the simplest approach, after fixing a small window aroundx_0, inference of peer effects in our model can be carried out through the following regression:

$$Y_i = \alpha + \beta x_i + \rho D_i + \eta_i \qquad Equation\ 2$$

Where ρ is the causal effect of interest. In Equation 2, our regressor of interest D_i is not only correlated with x_i, but it is a deterministic function of x_i as well. RDD captures causal effects by discriminating the nonlinear and discontinuous function, $1(x_i \geq x_0)$, from the smooth and (in this case) linear function, x_i. However, the trend relation between Y_i and x_i may be nonlinear. In this case, we can fit the following model:

$$Y_i = f(x_i) + \rho D_i + \eta_i \qquad Equation\ 3$$

Provided that $f(x_i)$ is continuous aroundx_0, it is possible to estimate Equation 3 even with a flexible functional form for $f(x_i)$. As illustrated by Angrist and Pischke (2008), modeling $f(x_i)$ with a p^{th}-order polynomial, RDD estimates can be obtained from the regression:

$$Y_i = \alpha + \beta_1 x_i + \beta_2 x_i^2 + \beta_p x_i^p + \rho D_i + \eta_i \qquad Equation\ 4$$

Beyond that, a generalization of RDD allows for a differential trend between treated and non-treated individuals:

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[6]As mentioned in the previous footnote, D_i may not be deterministic since students may choose not to enroll. D_i does tell which class the student is assigned to if he/she chooses to enroll. Nevertheless, for simplicity we chose to keep the illustration of our methodology with the sharp scenario.

$$Y_i = \alpha + \beta_1 D_i + \beta_2 x_i + \beta_3 D_i x_i + \gamma_p + \gamma_k + \gamma_t + \varepsilon_i \qquad Equation\ 5$$

where Y_i is the academic performance measure for student i, D_i is a dummy variable indicating the semester the students belongs to (1=first semester; 0=second semester), x_i is the standardized assignment grade and γ_p represents teacher fixed effects. Aiming at improving our estimators' efficiency we will include fixed effects for courses (γ_k) and time (γ_t).

When working with the data we will test and therefore define both the functional form of the model and the bandwidths that best fits the data.

3 Expected Outcomes

Based on the literature applied to peer effects on higher education, we may expect to identify the existence of impacts of peers on student's academic outcomes. Given a different university context and the diverse directions of peer effects on College students' achievements (verified in studies based in national and international College students), we believe it is more advisable to analyze the data before speculating the directions and heterogeneities in peer effects that we might find.

4 References

Ali M. M., Dwyer D. S. (2009). Estimating peer effects in adolescent smoking behavior: A longitudinal analysis. *Journal of Adolescent Health,* 45:402-408.

André, D. de M. (2016). Peer Effects and Academic Performance in Higher Education - A Regression Discontinuity Design Approach. In: André, D. de M. *Three essays on applied microeconometrics with spatial effects (Doctoral dissertation)*.Retrieved from Federal University of Ceara (UFC) Institutional Repository. Available at: http://www.repositorio.ufc.br/bitstream/riufc/19363/1/2016_tese_dmandr%C3%A9.pdf. Accessed on: 04/22/2017.

Angrist, J. D. and Pischke, J. S. (2008). Getting a Little Jumpy: Regression Discontinuity Designs. In Angrist, J. D. and Pischke, J. S., *Mostly Harmless Econometrics: An Empiricist's Companion*. Business Economics, 45(1):75–76.

Asadullah, M., and Chaudhury, N. (2008). Social Interactions And Student Achievement In A Developing Country: An Instrumental Variables Approach. *Policy Research Working Papers*. http://dx.doi.org/10.1596/1813-9450-4508.

Burke, M. A. and Sass, T. R. (2013). Classroom Peer Effects and Student Achievement. *Journal of Labor Economics*,31(1): 51-82. doi: 10.1086/666653.

Campos, C., Hargreaves Heap, S., and Leite Lopez de Leon, F. (2016). The political influence of peer groups: experimental evidence in the classroom. *Oxford Economic Papers*, gpw065. http://dx.doi.org/10.1093/oep/gpw065.

Carrell, S. E., Fullerton, R. L., and West, J. E. (2009). Does Your Cohort Matter? Measuring Peer Effects in College Achievement. *Journal of Labor Economics*, 27(3), 439-464.

Carrell, Scott E., and Mark L. Hoekstra.(2010). Externalities in the classroom: How children exposed to domestic violence affect everyone's kids. American Economic Journal: Applied Economics 2(1):211–28.

Chen, Q., Okediji, T. and Guoqiang, T. (2015). Exploiting Regression-Discontinuity Design to Estimate Peer Effects in College – The Case of Class Attendance. *Economics Bulletin*, 35(3):1563-1571.

Chetty, R., Friedman, J., Hilger, N., Saez, E., Schanzenbach, D. W. and Yagan, D. (2011). How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star. *The Quarterly Journal of Economics*, 126(4): 1593-1660.

Cornelissen, T., Dustmann, C. and Schönberg, U. (2017). Peer Effects in the Workplace. *American Economic Review*, 107(2): 425–456.

Dahl, G., Løken, K., and Mogstad, M. (2014). Peer Effects in Program Participation. *American Economic Review*, *104*(7), 2049-2074. http://dx.doi.org/10.1257/aer.104.7.2049.

De Melo, G. (2014). Peer effects identified through social networks: Evidence from Uruguayan schools. *Working Papers, Banco de México*, No. 2014-05.

DeLay, D., Hanish, L. D., Martin, C. L., and Fabes, R. A. (2016). Peer effects on Head Start children's preschool competency. *Developmental Psychology*, 52(1), 58–70.

Duflo, E., Dupas, P., and Kremer, M. (2011). Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya. *American Economic Review*, *101*(5), 1739-1774. http://dx.doi.org/10.1257/aer.101.5.1739.

Eisenberg, D., Golberstein, E. and Whitlock, J. L. (2014). Peer effects on risky behaviors: New evidence from college roommate assignments. *Journal of Health Economics*, 33: 126-138.

Fortin B, Yazbeck M. (2015). Peer effects, fast food consumption and adolescent weight gain. *Journal of Health Economics,* 42: 125–138.

Gaviria, A., Raphael, S.(2001). School-based peer effects and juvenile behavior. *Review of Economics and Statistics,* 83 (2), 257–268.

Graham, B. (2011). Econometric methods for the analysis of assignment problems in the presence of complementarity and social spillovers. In J. Benhabib, M. O. Jacksons and A. Bisin (Eds.), *Handbook of Social Economics*. Amsterdam: North-Holland.

Hanushek, E., Kain, J., Markman, J., and Rivkin, S. (2003). Does peer ability affect student achievement?. *Journal Of Applied Econometrics*, 18(5), 527-544. http://dx.doi.org/10.1002/jae.741.

Imbens, G. W., and T. Lemieux.(2008). Regression Discontinuity Designs: A Guide to Practice. *Journal of Econometrics*, 142(2): 615–35.

Kremer, M. and Levy, D. (2008). Peer Effects and Alcohol Use among College Students. *Journal of Economic Perspectives*, 22(3): 189–206.

Lee, D. S. and Lemieux, T.(2010). Regression discontinuity designs in economics. *Journal of Economic Literature,* 48, 281-355.

Lee, D. S. and Lemieux, T.(2015). Regression Discontinuity Designs in Social Sciences. In *Regression Analysis and Causal Inference*, H. Best and C. Wolf (eds.), Sage.

Manski, Charles F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3):531-42.

Mas, A., and Moretti, E. (2009). Peers at work. *American Economic Review*, 99, 1: 112-145.

Matta, R., Ribas, R. P., Sampaio, B. and Sampaio, G. (2016). The effect of age at school entry on college admission and earnings: a regression-discontinuity approach. *IZA Journal of Labor Economics*, 5:9. doi: 10.1186/s40172-016-0049-5.

Mehrotra, S. (2012). The cost and financing of the right to education in India: Can we fill the financing gap. *International Journal of Educational Development*, 32(1): 65–71. (doi:10.1016/j.ijedudev.2011.02.001)

Ministério da Educação (MEC) and Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira (INEP). (2016). *Censo da Educação Superior: Sinopse Estatística da Educação Superior - Graduação*. Brasília, DF. Available at: http://portal.inep.gov.br/sinopses-estatisticas-da-educacao-superior. Accessed on: 04/23/2017.

Moretti, E. (2011). Social learning and peer effects in consumption: evidence from movie sales. *The Review of Economic Studies*, vol. 78(1), pp. 356–93.

Neidell, M., and Waldfogel, J. (2010). Cognitive and Noncognitive Peer Effects in Early Education. *The Review of Economics and Statistics*, 92(3): 562-576. doi: 10.1162/REST_a_00012.

Poldin, O., P. Simoes, T. P.,Knobel, M. and Yudkevich, M. (2015). Estimation of Peer Effects with Predicted Social Ties: Evidence from two Universities in Brazil and Russia. National Research University. Higher School of Economics. Basic Research Program.*Working Papers Series: Education*,WP BRP 30/EDU/2015.

Ranking Universitário Folha (RUF).(2016). *Folha de São Paulo*. Available at: http://ruf.folha.uol.com.br/2016/ranking-de-universidades/. Accessed on: 12/05/2017.

Rossetto, C. B. de S.; Gonçalves, F. de O.(2015). Equidade na Educação Superior no Brasil: Uma Análise Multinomial das Políticas Públicas de Acesso. *Dados - Revista de Ciências Sociais*, 58(3): 791-824. Universidade do Estado do Rio de Janeiro. Rio de Janeiro, Brasil.

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? In Erik Hanushek, Stephen Machin and Ludger Woessmann (ed.). *Handbook of the Economics of Education*, Elsevier, edition 1, volume 3, 249-277. ISSN 0169-7218, DOI: 10.1016/S0169-7218(11)03004-8.

Soetevent, A. (2006). Empirics of the identification of social interactions: An evaluation of the approaches and their results. *Journal of Economic Surveys*, 20(2):193 - 228.

Times Higher Education (THE).(2016). *World University Rankings*. Available at: https://www.timeshighereducation.com/world-university-rankings/federal-university-minas-gerais#ranking-dataset/584703. Accessed on: 12/05/2017.

Trogdon, J., Nonnemaker, J., and Pais, J. (2008). Peer effects in adolescent overweight. *Journal Of Health Economics*, *27*(5), 1388-1399. http://dx.doi.org/10.1016/j.jhealeco.2008.05.003.

Yakusheva, O.,Kapinos, K. A., Eisenberg, D.(2014). Estimating Heterogeneous and Hierarchical Peer Effects on Body Weight Using Roommate Assignments as a Natural Experiment. *Journal of Human Resources*, Volume 49, Number 1, Winter 2014, pp. 234-261.

Zimmerman, David J. (2003). Peer effects in academic outcomes: Evidence from a natural experiment. *Review of Economics and Statistics,* 85, no. 1:9-23.