FUNDAÇÃO GETULIO VARGAS
ESCOLA DE ECONOMIA DE SÃO PAULO

VINICIUS GOMES DE LIMA

PEER EFFECTS IN ACTIVE LEARNING

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Dissertação apresentada à Escola de Economia de São Paulo da Fundação Getulio Vargas como requisito para obtenção do título de Mestre em Economia de Empresas

Campo de Conhecimento:
Economia da educação

Orientador: Prof. Dr. Vladimir Pinheiro Ponczek

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ABSTRACT

This paper investigates peer effects in higher education in an environment of *active learning* that gives great importance for students' interaction through group work. Our empirical strategy uses exogenous variation in group composition to estimate peer effects in different exercises. We find no evidence of peer effects in a basic linear-in-means specification considering all assigned peers. However, we find positive and statistically significant impact of peers coming from student's same high school. We also find no evidence of peer effects with a model that takes into account student and peers' position in the ability distribution.

Keywords: Peer effects, active learning, higher education.

RESUMO

Este trabalho investiga efeito de pares no ensino superior em um ambiente de *active learning* que dá grande importância à interação dos estudantes através do trabalho em grupo. A estratégia empírica utiliza variação exógena na composição dos grupos para estimar o efeito dos pares em diferentes exercícios. Não encontramos evidência de efeito de pares numa especificação *linear-in-means* básica considerando todos os pares do grupo atribuído ao aluno. Entretanto, encontramos efeito positivo e estatisticamente significante de pares que frequentaram a mesma escola de ensino médio. Não encontramos evidência de efeito de pares em um modelos que procura considerar a posição dos alunos na distribuição de habilidade.

Palavras-chave: Efeito de pares, *active learning*, ensino superior.

List of Tables

Contents

1 Introduction

People have always lived in groups. As such, interpersonal interactions may have a prominent role in explaining individual preferences and the decision making process. Durlauf e Young (2001) argue that through its methods, economics can be useful for deepening the understanding of outcomes resulting from interactive behavior.

The study of group effects over individual behavior has been an active topic of research in the economics of crime, health, labor, education and many other fields.[1] In education, peer effects should be considered when discussing vouchers, community (and school) choice, ability tracking and other issues.[2] Specifically in higher education, several papers tried to estimate peer effects making use of roommates assignment to identify potentially relevant peers and then estimate the impact a student may have on his colleague. For instance, Sacerdote (2001) uses random assignment of roomates and dormmates in Dartmouth College to investigate peer effects over different outcomes. He finds that roommates with an academic score in the top 25% positively affect students' GPA compared to having a roomate among the bottom 25% in this score. He also finds that dormmates' membership of social organizations affect decisions to join social groups more strongly than do roomates' membership. Exploring a similar assignment mechanism, Zimmerman (2003) finds positive impact of roommates' verbal ability on GPA for students in the middle 70% of the ability distribution. He also finds that in this range of ability, men and women are affected differently. Men are negatively impacted if assigned to a roommate who is among the lowest 15% in the verbal ability distribution. However, girls benefit from having a peer among the lowest 15% in the math ability distribution. Foster (2006) uses students' residential community random assignment as instrument for group formation. She finds that impacts on students' GPA steming from peers who would be socially closer is not much different of impacts coming from randomly attributed peers.

In order to estimate peer effects, all the above mentioned papers had to define a student's peer group from the available information. But these information may not reveal who are the most important peers for outcomes of interest in the analysis. That is, roomates may be only a subset of the people who influence a given student's behavior. Carrell, Fullerton e West (2009) are able to analyze peer groups with whom individuals interact most of their time and they find positive effects larger than those estimated by the roommates' papers. This selected literature highlights that

[1] See, for example, Bayer, Hjalmarsson e Pozen (2009), Trogdon, Nonnemaker e Pais (2008) and Mas e Moretti (2009)

[2] Epple e Romano (2011) survey many theoretical models and Sacerdote (2011) discuss some of the empirical findings in the literature of peer effects in education.

knowing the relevant peer group is crucial to the analysis and that so far estimates of peer effects have been somewhat constrained by data availability. As noted by Stinebrickner e Stinebrickner (2006), it is important to be "looking at the right place" when studying peer effects. First, they state that students arriving "at school with strong academic ability, good study habits, and strong beliefs about the importance of college may substantially mitigate the potential influence of peer effects". Besides, to circumvent methodological problems, empirical works have been analyzed the relationship between exogenously atributted peers, as in the example of roommates. But actually students can look for partners more suitable to their needs than this random peers. Finally, using measures of academic ability as the relevant peer characteristic would be not enough to capture variation in types of behavior that impacts most one's performance.

In our paper, we investigate peer effects in a selective higher education institution in Brazil that adopted a method of *active learning* in its economics undergraduate course. Particularly, we look to students interacting under the method of *problem based learning*, which put group work at the core of the learning process. We come back to this in the next section. It will be clear that students in our data match the student's profile described by Stinebrickner e Stinebrickner (2006). But the undergraduate course structure we analyze implies that peers are true inputs to individual performance. Even though students can interact with whoever they want outside class, the environment we analyze gives much incentive for interaction with the partners exogenously assigned to them. We discuss later in the paper how the assignment works and show that students have incentives to interact with the assigned peers. Besides, the assignment rule allows us to deal with some potential threats to identification (something we also discuss later). Lastly, the variables we use to capture peers' characteristics may not contain all relevant aspects that influence one's performance. But some baseline regressions show that they are anyway important in explaining students' performance. Summing up, we believe to be "looking at the right place" and the empirical strategy employed in the paper uses exogenous variation in group composition to identify peer effects. We look to reduced form linear-in-means specification and in the baseline models we find no evidence of peer effects. Each group analyzed is supervised by a tutor and we find no evidence that a more experienced tutor boosts peer effects. What we find is that having classmates coming from the same high school and with good ability in writing benefits students' performance. Exercises looking for possible nonlinearities in peer effects also do not find statistically significant results.

The paper organizes as follows. Next section describes what is active learning and the specific setting we analyze. Section 3 presents the data, section 4 discusses the empirical strategy and section 5 shows and analyzes results. We conclude in section 6.

2 Active Learning

2.1 What is Active Learning?

The defining feature of active learning is the use of instructional practices that engage students in the learning process (PRINCE, 2004). A central element is the introduction of activities into the classroom so that students departure from the passive position of knowledge receivers to become the main agents responsible for their learning process. The problem-based learning (PBL) is a type of active learning that uses problems to start and motivate the learning process. As there are many different strategies to involve students in this process through problems, it is unlikely that a narrow definition of PBL encompasses all experiences with the method. However, Barrows (1996) lists six core elements of PBL:

1. Learning is student-centered
2. Learning occurs in small student groups
3. A tutor is present as a facilitator or guide
4. Authentic problems are presented at the beginning of the learning sequence and before any preparation or study has occurred
5. The problems encountered are used as tools to achieve the required knowledge and the problem-solving skills necessary to eventually solve problems
6. New information is acquired through self-directed learning

Even when these elements are met, different possibilities of implementation makes it hard to find some definitive evidence about PBL effectiveness in terms of influencing learning outcomes. The large variation found across the settings analyzed gives rise to many factors that may matter: cooperation/competition, collaborative/individual work, group size and so on. As summarized by Gijbels et al. (2005), reviews of PBL effects on students' motivation and attitude is generally positive, but effects on knowledge acquisition is only limited.

Nevertheless, in this paper we do not intend to evaluate how PBL performs when compared to a traditional learning environment. What is important to the analysis here is the relevance of group work in a PBL environment and in particular how PBL at FGV/EESP put group interaction at the core of learning process. This provides a meaningful mechanism for the influence that peers may have on a student's individual performance. The next section details the features of FGV/EESP's use of problem-based learning.

2.2 Problem-based Learning at FGV/EESP

São Paulo School of Economics (EESP) was created in 2003 as part of Getulio Vargas Foundation (FGV), a leading think tank and higher education institution created in 1944 in Brazil.[1] The school experienced a rapid growth, becoming one of the leading Brazilian departments in economic research and offering the best undergraduate course in economics in Brazil.[2] Each year, up to 60 students are admitted from a highly selective admission exam done by around 1,500 candidates. The annual tuition for 2016 was approximately three times greater than the Brazilian per capita income calculated for that year and two times greater than per capita income in São Paulo state.[3] To make a comparison, according to a consulting firm, in 2014, the average tuition in Brazil was 60% of country's per capita income and in São Paulo it was 40% of state per capita income.[4] In order to guarantee that no good student be left out due to lack of resources, FGV offers scholarships to those with high achievement in the admission exam and loans to every student in need. This implies that the analysis undertaken in this paper has limited external validity regarding higher education in general, though it may shed light over important aspects of educational production.

The main motivation for the adoption of PBL at FGV/EESP was that, from school's point of view, traditional teaching culture was not enough to prepare professionals with the abilities required by the labor market. The idea was that students should leave the school being capable of using economic models to understand and solve problems in real situations. Table (2.1) shows the schedule of implementation of PBL at FGV/EESP.

In the model adopted in 2013 and still at work, each course (discipline) in the school has up to 60 students enrolled. This group of students is divided in small subgroups that will work together throughout the semester (or quarter for some courses). Each week, the whole group have a lecture with the teacher responsible for the course (the leading teacher) and then each subgroup work separately in the tutorial sessions.[5]

[1] According to the *Global Go To Think Tank* of the University of Pennsylvania, FGV is the top think tank in Latin America and one of top ten in the world.

[2] https://ideas.repec.org/top/ top.brazil.html; EESP had the best performance in IGC 2015, an evaluation conducted by the Ministry of Education.

[3] *Annual tuition in 2016: R$ 45,096; Pesquisa Nacional por Amostra de Domicílios Contínua* 2016

[4] http://ultimosegundo.ig.com.br/educacao/2014-06-15/valor-medio-da-mensalidade-de-faculdades-cresce-4-em-2014-e-alcanca-r-645.html

[5] For some courses, there is no more lectures, only the tutorial sessions.

2011	visit to Maastricht University and presentation of PBL to professors
2012	visit at Aalborg University; defining the trial, tutors training and preparation for curricula change, preparation of workbooks; trial evaluation;
2013	PBL in mandatory disciplines from first and second semesters;
2014	PBL in mandatory disciplines from third and fourth semesters;
2015	PBL in mandatory disciplines from fifth and sixth semesters;
2016	100% of curriculum completed and elected disciplines.

Table 2.1: PBL Implementation Schedule at FGV/EESP

In the *pre-discussion session*, a real world problem is presented to the students with no requirement of specific previous work on the topic. They start discussing some concepts to analyze the problem and one student will be responsible for recording the concepts discussed and the questions raised and for summing up conclusions. Another student will be the leader of this session. His task is to organize the content and to ensure the opportunity for all colleagues to participate in the session.

Each group will have a *tutor* who will guide and stimulate the pre-discussion session with questions. The tutor is not going to give a lecture, his role will be coaching students through the problem so that students themselves formulate the learning objectives at the end of the session. Knowing the learning objectives, the students have some days to work before the next session.

The *post-discussion* session then takes place and students should respond to the problem in a systematic manner, using precise concepts, so they can conclude the discussion initiated in the previous session. Once the job is done, the tutor must evaluate the performance and give appropriate feedback so that students know exactly what they need to improve their competences and to perform better.

Some particularities of how PBL was implemented at FGV/EESP are important to our analysis. First, students' performance in tutorial sessions has direct impact in their final grade. At the end of each session, the tutor evaluates each student by giving him a grade between 0 and 1. The mean of these grades are then used as a multiplicative factor over the mean obtained from different evaluations. This way, the better the performance in group work, the better his overall performance in terms of the final grade in the course. This provides a strong incentive for the students to participate actively during tutorial sessions, what makes peers an important part of the learning process. Besides, students do not choose the tutorial group to which they will belong. This is a crucial feature for our identification hypothesis. The next subsection discusses the assignment rule that forms the groups.

2.2.1 Students Assignment to Groups

Each course has a specific rule to form the subgroups that will work together in the tutorial sessions. All the rules were designed to balance the composition of the subgroups in terms of previous performance. By previous performance we mean the result in the admission exam for the first period of the course and GPA for subsequent periods. An example makes things clearer.

In their first period, every student must do *Course 1*.[6] The school ranks them according to their performance in the admission exam and form the subgroups of this class by following the pattern shown in the table (2.2).

A	1	5	9	13	17	21	25	29	33	37	41	45	49	53		
B	2	6	10	14	18	22	26	30	34	38	42	46	50	54		
C	3	7	11	15	19	23	27	31	35	39	43	47	51	55	57	59
D	4	8	12	16	20	24	28	32	36	40	44	48	52	56	58	60

Table 2.2: Assignment Rule

It means that the student with the best performance among those enrolled in the course goes to group *A*, the student in the second place goes to group *B* and so on. The only difference for subsequent periods is that GPA is the information used to rank the students. Though the patterns differ across courses, for a given course it has not changed during the period analyzes.

Of course a student influences his position in the ranking, but it is unlikely that it could be done so that he can determine the groups to which he will be assigned. Moreover, students do not know the assignment mechanism. Two relevant points are that the rule was strictly followed and that no student was relocated from the group he was assigned. To check if students and peers ability are in someway related to group formation, table (2.3) below shows regression of student's ability on peers' ability. We regress student's writing ability on peers' math ability and student's math ability on peers' writing ability to avoid a mechanical correlation: in a given group, peers' mean ability in math will be maximum for the student with lowest ability and minimum for the student with the highest ability, for example. The results show that groups are not formed by gathering students with similar ability, as is expected if there is compliance with the assignment rule.

[6]We omit the names of disciplines to avoid the possibility of students getting to know that.

Table 2.3: Correlation between student and peers' ability

	Writing	Mathematics
Ranking	-0.007***	-0.013***
	[0.001]	[0.001]
Math	-0.056	
	[0.118]	
Writing		0.035
		[0.082]
Observations	3197	3197

Dep. variable is student's own ability and regressor is peers' mean ability. We run *writing* on *math* and vice-versa to avoid mechanical correlation.
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3 Data

We use data of students in courses that adopted PBL after 2013. Students were admitted mainly after 2013, but there is also information on some students admitted before 2013. These students are either doing a course again or enrolled in delay. We observe 74 students from cohorts admitted before 2013 and they represent 3.6% of the available observations. For each student we know gender, race and income level from a socioeconomic questionnaire filled out when they subscribe to the admission exam. However, socioeconomic information is not available for students admitted from 2008 to 2012 (except from gender). For 2008 and 2009, the questionnaire did not have questions on race and income and for 2011 and 2012, the questionnaire was not applied. For 2010 there is information only about income but in a different scale. We also know students' high school. This is used to control school fixed-effects and to build a variable identifying people who potentially had already had some kind of interaction before getting into college.

Every year, the admission exam was developed by VUNESP, a renowned Brazilian public institution responsible for several other exams including the admission exam of UNESP, a public state university of São Paulo. The exam is applied in two days and the subjects covered are: mathematics, biology, history, geography, english, physics, chemistry, portuguese language. In the first day they solve 135 questions on these subjects and two weeks later they must answer 12 discursive questions: 4 in mathematics and 8 in portuguese language. In this second day they must also do a written essay. The exams are comparable across the years. We will use as a measure of ability the scores on mathematics from first day (tests) and the performance on the written essay. We standardize these scores among the students invited to enroll, i.e., not necessarily those who ended up enrolling in FGV/EESP. The choice of mathematics and writing in part follows previous literature that uses math and verbal scores of SAT.[1] But these subjects may also cover the main skills needed to succeed in the courses. Mathematics is assumed to be a measure of the logical and quantitative reasoning skills demanded from the core disciplines. Writing should be relevant since students are assessed mainly through written exams. Also, the ability of exposing ideas and formulating arguments may be important in group work.

Administrative records provide the year of entry, the proportion of monthly fee received as loan in each semester and student's performance in each of the courses taken. When we refer to *loan* we mean a funding students receive after an analysis of socioeconomic background and that must be repaid after graduating. According to the staff, this analysis do not take performance into account

[1] Sacerdote (2001) and Zimmerman (2003), for instance

in any way. By performance we mean final grades and its two main parts: (i) intermediate and final exams and (ii) participation grade.[2]

An additional variable for the students indicate the tutorial group to which they were assigned in each course. Two characteristics of the groups are observed. The first is the tutor of the group, who is sometimes responsible for more than one group in a given semester. It is also possible that a tutor shows up in different years. The other aspect is that the leading teacher is always tutor of at least one group and so we created a variable to indicate if the student is in the teacher's group. For each course, besides knowing who is the leading teacher, we know the workload and the share of this time that is formally spent in group work. Tables (3.1) and (3.2) show descriptive statistics.

[2]Some courses may have more than one intermediate exam or other types of evaluation. There are also courses with no intermediate evaluation. Usually, final exams are given 60% of the final grade (before applying the participation factor). Final grade is obtained from the weighted average of (i) multiplied by a factor between 0 and 1 corresponding to (ii). Participation grade, in turn, is an average of the performance in each tutorial sessions. The tutor of the group should assess individual engagement and contribution for the development of the session. Student's absence implies a 0 for the session missed. For a given course, if there was n tutorial sessions, the $n/7$ lowest participation grades are discarded when computing the final participation grade. For example, if there were 28 sessions in a course, the 4 lowest marks are discarded.

Table 3.1: Descriptive Statistics - Carachteristics by cohort

	2013			2014			2015			2016		
	Mean	Std. Dev	N	Mean	Std. Dev	N	Mean	Std. Dev	N	Mean	Std. Dev	N
Socioeconomic												
Female	0.31	0.47	55	0.40	0.50	52	0.25	0.44	51	0.22	0.42	46
Black	0.04	0.19	55	0.08	0.27	52	-	-	51	0.07	0.25	46
Income Levels												
Level 1	0.05	0.23	55	0.06	0.24	52	0.14	0.35	51	0.07	0.25	46
Level 2	0.25	0.44	55	0.17	0.38	52	0.14	0.35	51	0.11	0.31	46
Level 3	0.13	0.34	55	0.17	0.38	52	0.20	0.40	51	0.17	0.38	46
Level 4	0.29	0.46	55	0.19	0.40	52	0.16	0.37	51	0.17	0.38	46
Level 5	0.09	0.29	55	0.17	0.38	52	0.14	0.35	51	0.11	0.31	46
Level 6	0.18	0.39	55	0.23	0.43	52	0.24	0.43	51	0.37	0.49	46
Ability												
Mathematics	6.08	0.73	55	5.96	0.87	52	6.29	0.81	59	5.99	0.76	46
Writing	5.15	0.90	55	5.20	1.00	52	5.19	1.00	59	5.26	0.97	46
Ranking (median)	77		55	98		52	65		59	68		46

Notes: Socioeconomic information is not available for students admitted from 2008 to 2012 (except gender).
For 2008 and 2009, the questionnaire did not have questions on race and income; for 2011 and 2012, the questionnaire was not applied. For 2010 there is information only about income but in a different scale.

Table 3.2: Descriptive Statistics - Academic information by year

	2013			2014			2015			2016		
	Mean	Std. Dev	N	Mean	Std. Dev	N	Mean	Std. Dev	N	Mean	Std. Dev	N
Loan (if $\neq 0$)												
1^{st} semester	0.79	0.21	17	0.71	0.28	20	0.76	0.26	27	0.72	0.28	33
2^{nd} semester	0.73	0.21	15	0.73	0.27	18	0.75	0.26	32	0.74	0.26	28
Final Grade	6.36	2.59	552	6.14	2.54	755	6.42	2.6	1049	6.76	2.28	1150
Participation	0.98	0.07	508	0.99	0.07	677	0.99	0.07	836	0.99	0.04	1066
Final Exam	7.12	2.14	458	6.67	1.68	584	6.75	1.73	904	6.91	1.78	986
First Exam	6.93	1.93	342	6.72	1.75	493	7.03	1.84	621	7.11	2.05	805
Groups			38			59			86			97
Courses			10			18			29			32
Group Size	14	1.55		13	2.46		12	2.07		12	2.04	

Notes: Information on *loan* is shown for those who receive it (different from zero).
A student is observed in more than one course, then $N = student \times courses$.

Table (3.1) summarizes the characteristics of the cohorts admitted after 2013. The proportion of women ranges from 20% to 40%. People self reported as black are at most 8% of students in the data.[3] For 2015, the question about race was not included in the questionnaire. Information of family income is only available as proportions of students falling into some intervals. The mean of level 1 indicates the proportion of students with family income below the threshold of 10 minimum wages.[4] The thresholds for the other levels are multiples (2, 3, 4 and 5) of this value. Level 6 comprises students with family income above 50 minimum wages. We see that most of the students does not seem to come from a disadvantaged socioeconomic background. In terms of measured ability, mean achievement across cohorts are fairly similar but there is some variation in the ranking of enrolled students.

Socioeconomic information is not available for students admitted from 2008 to 2012 (except from gender). For 2008 and 2009, the questionnaire did not have questions on race and income; for 2011 and 2012, the questionnaire was not applied; and for 2010 there is information only about income but in a different scale.

Information on table (3.2) is separated not by cohorts, but by academic year. It contains information for each student in each course he has taken in the year indicated on top. The only figure summarized for each individual is loan, since it varies semiannually. In this case, N is indicating how many students in our data received loan in each semester and the mean column indicates the mean proportion on monthly fee received as loan by these students.

Table (3.3) shows correlations between the standardized final grade and the variables to be used as controls in the results. Ability is highly correlated with performance and girls have higher achievement. The observed difference for men and women is increased once regression is controlled for school fixed effects. The estimates for these three variables are all statistically significant. It is worthy noting that inclusion of a dummy for race does not add much to explain performance as evidenced by the R^2. It is also not possible to reject that the estimated coefficient is different of zero. This is not a surprising result, since descriptive statistics shows that there are few self reported black people. Additionally, we lose some observations due to the absence of the question on race in 2015 questionnaire. The estimated coefficients for income levels are not statistically significant, neither individually nor jointly. Without income dummies, loan may seem to act as a proxy for it. This would be the case if we consider that proportion of loan is higher for those students with lower income and that income is positively correlated with performance. Thus, for the results shown from now on we use the variables in model (5) as main controls.

[3] *Negros* and *pardos*.

[4] Approximately US$360 in PPP for 2012, the year when students subscribed for 2013.

Table 3.3: OLS Baseline

	Dependent Var.: Standardized Final Grade				
	(1)	(2)	(3)	(4)	(5)
Ability					
Writing	0.144***	0.178***	0.150***	0.152***	0.173***
	[0.035]	[0.042]	[0.047]	[0.036]	[0.050]
Mathematics	0.185***	0.187***	0.188***	0.182***	0.185***
	[0.033]	[0.038]	[0.055]	[0.033]	[0.056]
Characteristics					
Female	0.172***	0.144*	0.320***	0.161**	0.308***
	[0.066]	[0.077]	[0.109]	[0.067]	[0.114]
Loan	-0.014	-0.058	-0.043	0.045	0.108
	[0.099]	[0.110]	[0.130]	[0.124]	[0.150]
Black		-0.121			
		[0.210]			
Income Levels					
Level 2				0.067	0.330
				[0.179]	[0.280]
Level 3				0.012	0.219
				[0.174]	[0.288]
Level 4				0.100	0.476
				[0.186]	[0.297]
Level 5				0.161	0.352
				[0.183]	[0.282]
Level 6				0.085	0.321
				[0.185]	[0.294]
School FE	No	No	Yes	No	Yes
R^2	0.097	0.103	0.271	0.099	0.270
Observations	3152	2465	3065	3045	3010

Standard errors clustered by student in brackets

Year, cohort, course and tutor fixed-effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Empirical Strategy

The econometric approach for most of the empirical works mentioned above rely on the linear-in-means model, which is the baseline for our analysis. In a framework of interactions, choices can be seen as the outcome of an individual maximization process that takes into account the expected behavior of other individuals. In such a context, the linear-in-means specification is consistent with a model in which an individual try to minimize the deviation of his behavior from a linear function of group's mean behavior (BROCK; DURLAUF, 2001). We follow Boucher et al. (2014) by defining as *peer* a student i whose academic performance and personal characteristics may affect the performance of other student j in the same group. To discuss the challenges in estimating peer effects consider the following structure.

Suppose there exists G groups indexed by $g \in \{1, ..., G\}$, each of them containing n_g individuals indexed by $i \in \{1, ..., n_g\}$. Define $P_i = \{1, ..., n_g\} \setminus \{i\}$, the group of i's peers. Then, for a given group we have a system formed by individual equations like

$$y_{ig} = \alpha + \beta \underbrace{\frac{\sum_{j \in P_i} y_{jg}}{n_g - 1}}_{\tilde{y}_{ig}} + \gamma x_{ig} + \delta \underbrace{\frac{\sum_{j \in P_i} x_{jg}}{n_g - 1}}_{\tilde{x}_{ig}} + \varepsilon_{ig}. \tag{1}$$

In education, y may be a measure of student's achievement and x a measure of ability.[1] The parameter γ captures the effect of student's own ability on his achievement. In the terms of Manski (1993), β captures how individual behavior vary with the prevalent behavior in the group, the *endogenous effect*. But individual behavior also vary with exogenous characteristics of the group, and this is the *contextual* or *exogenous effect* captured by the parameter δ. A third effect may arise from the fact that individuals in the same group tend to be similar due to similar individual characteristics or to sharing similar institutional environments, the *correlated effect*. A group fixed effect in the equation could capture what is constant for peers of the same group.

With information on ability, provided that $|\beta| < 1$, through OLS we could only estimate a reduced form that does not allow us separating endogenous and contextual effects. The reduced

[1] Here, for simplicity, we use a single characteristic without loss of generality for ease of exposition.

form for a given individual of some group is

$$y_{ig} = \underbrace{\frac{\alpha}{1-\beta}}_{\pi_0} + \underbrace{\left[\gamma + \frac{\beta\,(\gamma\beta+\delta)}{(n-1+\beta)(1-\beta)}\right]}_{\pi_1} x_{ig} + \underbrace{\left[\frac{\gamma\beta+\delta}{(1+\frac{\beta}{n_g-1})(1-\beta)}\right]}_{\pi_2} \tilde{x}_{jg} + \varepsilon_{ig}. \tag{2}$$

See that student's own ability affects him directly through γ but also through feedback effects. Regarding social effects, despite the impossibility of separating endogenous from contextual effects, $\pi_2 \neq 0$ would imply the presence of peer effects, since it is reasonable that $\gamma \neq 0$.

This is a simultaneity problem that became known in the literature as the reflection problem (MANSKI, idem). It refers to the process in which a person's outcome is affected by the outcome of others as well as the other way round. We discuss later in the paper some methods that can be used to separate the components of peer effects. Some additional basic problems potentially present in any attempt of estimating the effects of social interactions are endogenous membership and correlated unobservables (MOFFITT et al., 2001).

Endogenous membership occur when students can choose the group to which they belong. If that is so, estimates of peer effects may suffer from bias due to common unobservables determining selection and affecting outcomes. In our context, it does not seem a threat to identification, since group assignment is done according to an exogenous rule that was strictly followed as already mentioned.

The problem of correlated unobservables is present when some group-specific feature that explain the outcome is correlated to characteristics assumed exogenous. This could in part result from endogenous membership, what we rule out due to the assignment mechanism. The other source of correlation could arise from common factors affecting members of a group. In our case, it is possible that students selected in different years face different institutional environments due to reorganization of course sequence or changing rules, for example. We control this by using cohort fixed-effects. Further common factors affecting the groups of students formed are teachers and tutors, but we can observe them accurately. By using these controls, we expect to address the issues of correlated effects.

In our setting, the source for identification of peer effects (π_2) is the exogenous variation in the compostition of groups due to the exogenous assignment rule. Since allocation of students depends on their ranking, conditional on variables determining achievement (x) there is no unobservables explaining variations in $\tilde{x}$. However, this is not enough to estimate endogenous and contextual effects separately. In the appendix we report results for estimation of endogenous peer effects based on Boucher et al. (2014). But probably due to lack of enough variation in peers' variables we do not reach satisfying results.

To present the models we want to estimate, we define some notation. The variable y_{igct} is the achievement of student i, allocated in the group g of course c taken in period t. The vector $\mathbf{x}_{it}$ may contain student's ability measured in the admission exam (mathematics and writing) and characteristics (gender and loan). The vectors $\tilde{\mathbf{x}}_{igct}$ contain means for i's peers in the variables included in $\mathbf{x}_{it}$. Finally, $\mathbf{v}_{igct}$ controls for school, cohort, tutor and course fixed-effects when each applies.[2] The baseline is an OLS for a single equation model:

$$y_{igct} = \alpha_0 + \alpha_1 \mathbf{x}_{it} + \alpha_2 \tilde{\mathbf{x}}_{igct} + \varphi \mathbf{v}_{igct} + \varepsilon_{igct} \tag{3}$$

This is the linear-in-means reduced form in which y_{igct} is a measure of academic performance. The vector $\mathbf{x}_{it}$ contains student's own ability and characteristics. Information of peers are in the vector $\tilde{\mathbf{x}}_{igct}$, that contains ability or characteristics or both at the same time. Vector $\mathbf{v}_{igct}$ is composed by the variable of model (5) presented in table (3.3). Our interest is on coefficient α_2. Rejecting the null hypotheses for α_2 would evidence the presence of peers effects.

[2]Controlling for course fixed-effects is basically the same as controlling for teacher fixed-effects, since leading teachers rarely changed in the data.

5 Results

This section presents the results for the baseline equation presented above and for some exercises that extends it by incorporating the available information on data. To make a clear exposition, control variables are ommited from the tables but complete results are available in the appendix. We present results for the entire sample and for estimations restricted for first and second periods of student's first year at school. Results for first period may be more informative of a situation in which assigned peers may be more important, since most of the students do not known one another.

5.1 Basic Linear-in-Means

Table 5.1: Peer Effects on Final Grade

	All periods	1st period	2nd period
Peers			
Female	-0.086	0.099	0.285
	[0.140]	[0.275]	[0.372]
Loan	0.283	0.033	0.429
	[0.224]	[0.398]	[0.618]
Writing	-0.088	0.022	-0.098
	[0.082]	[0.124]	[0.199]
Mathematics	-0.032	-0.073	0.063
	[0.070]	[0.122]	[0.188]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table (5.1) shows results for equation (3) including peers' ability and characteristics. There is no evidence for the effect of peers' mean ability on individual performance measured by the final grade. Though not statistically significant, the point estimate show that peers' mean ability in writing would cause a decrease in performance by 0.09 standard deviations.

An increase of one standard deviation in writing would make a student approximately 11 positions above in the admission ranking. It means that for a given course, if all peers of a student were in average 11 position above in the admission ranking, that would make a student to lose one position in the ranking of that course (considering all enrolled students).[1] The coefficient on writing is similar in terms of magnitude to the impact of peers verbal ability estimated by Carrell, Fullerton e West (2009), but they find a positive effect. Looking to peers' characteristics, estimates are also not statistically significant. An average group of a given course has 12 people, and the point estimate of *Female* means that by adding a girl to the group would not cause a student to move in the course ranking. This negative estimate would be consistent with a model in which homegeneity in terms of gender is preferable. For the first two periods point estimates are positives, but standard errors are even higher and so we cannot reject zero impact of gender composition. The results also show that peers receiving loan would slightly benefit individual performance. If the average proportion of loan received by peers increased 10 points, it would raise individual performance by 0.029 standard deviation, what also would not change his position in the course ranking. Nonetheless, the estimates are also very imprecise. In the appendix we show results for models including ability and characteristics separately and estimates are qualitatively the same and similar in magnitude. The above table also show results restricting sample in the first two semesters, but precision gets worse as the number of observations decrease. Peers' writing ability would have positive impact in the first period and their math ability would make one's performance better in the second period. In the appendix we show results for this same specification but using the exams (first and final) as dependent variable instead of final grade. Estimates are not statistically significant, but in this exercise peers' ability seems more important in final exams.

The share of time spent in group work vary across disciplines. So we run models in which mean ability and characteristics of peers are weighted by this level of exposure, measured by the share of time in the course spent in tutorial sessions. Results are shown in table (5.2). Estimates using the entire sample are still statistically not significant, but reinforce what would be a negative peer effect for both ability measures. Now, results for fist period are also negative for ability. Analysis of estimates for characteristics are similar to that of table (5.1). A test for joint significance of peers's coefficients do not reject zero impact for both the "weighted" peer effects and the baseline model.[2]

[1]Peers with writing grade one standard deviation higher would be 11 positions better in the admission exam. For a student, this translates into a loss of $1 \times (-0.09) = -0.09$ standard deviation in final grade. For a given course, final grade one standard deviation lower causes a student to lose approximately 11 position. Thus, with the new group of peers, a student would be one position worse in the overall ranking of a discipline.

[2]In the appendix we show results for models using first and final exams as dependent variables. Peer effects in these cases seems to be positive, but again estimates are very imprecise.

Table 5.2: Peer Effects on Final Grade ("Weighted")

	All periods	1st period	2nd period
Peers			
Female	-0.184	-0.066	0.444
	[0.202]	[0.371]	[0.567]
Loan	0.255	-0.069	0.258
	[0.284]	[0.503]	[0.794]
Writing	-0.131	-0.038	-0.062
	[0.107]	[0.162]	[0.307]
Mathematics	-0.051	-0.024	0.048
	[0.093]	[0.166]	[0.268]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Teacher's Influence

We now run some exercises using the information on which tutorial group is conducted by the leading teacher. The motivation for this exercise is a conjecture about wheter supervision of a more experienced tutor would enhance group work. There could be two possible explanations for such a result. First, the teacher could in fact get more from students by coaching the session in a more effective way due to his or her experience. Or alternatively, students could feel obliged to work harder due to a perception that being directly observed by the leading teacher would imply a different assessement. To do this exercise we use the following model

$$y_{igct} = \alpha_0 + \alpha_1 \mathbf{x}_{igct} + \beta_1 T_{gct} + \gamma_1 (T_{gct} \times \mathbf{x}_{igct}) + \alpha_2 \tilde{\mathbf{x}}_{igct} + \gamma_2 (T_{gct} \times \tilde{\mathbf{x}}_{igct}) + \varphi \mathbf{v}_{igct} + \varepsilon_{igct} \quad (4)$$

where T_{igct} is equal 1 if the leading teacher is the tutor of group group g in course c and $T_{igct} = 0$ otherwise. This way we allow for different impacts of student's own variables and peers' means under the supervision of the leading teacher. Identification relies on the fact that students are attributed to teacher's group only by chance.

Results in table (5.3) for the full sample show that being in the teacher's group makes final grade to be higher. The achievement increases in 0.08 standard deviations and the estimate is statistically significant. This could be explained by the fact that evaluations are developed by the leading teacher

Table 5.3: Teacher Interaction: Student and Peers' ability

	All periods	1st period	2nd period
Student			
Writing	0.173***	0.190***	0.141
	[0.054]	[0.058]	[0.101]
Mathematics	0.211***	0.214***	0.271***
	[0.060]	[0.079]	[0.101]
Teacher	0.080*	-0.041	0.042
	[0.046]	[0.109]	[0.178]
Teacher* × *Student			
Writing	0.001	-0.043	0.063
	[0.033]	[0.049]	[0.081]
Mathematics	-0.070**	-0.047	0.089
	[0.035]	[0.058]	[0.078]
Peers			
Writing	-0.076	0.140	0.078
	[0.099]	[0.168]	[0.306]
Mathematics	-0.089	-0.165	-0.013
	[0.094]	[0.165]	[0.201]
Teacher* × *Peers			
Writing	-0.018	-0.283	0.010
	[0.139]	[0.236]	[0.381]
Mathematics	0.148	0.251	0.661
	[0.146]	[0.241]	[0.622]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and then students spending more time with him may be more able to understand what are the contents most relevant in teacher's point of view. Ability on mathematics is less important for students in teacher's group. Maybe teacher's presence may reveal something needed to good performance that, in other groups, would be only captured by people with better skills in math. Nonetheless, peers' mean ability in mathematics would be positive in teacher's group if $\alpha_2 + \gamma_2$ was jointly signinifcant (F statistics is only 0.31), what would be consistent with some of the two possibilities mentioned when introducing the exercise. Overall, peer effects are not statistically significant. Estimates for peer effects for this same model replacing ability by characteristics (appendix) are also not statistically significant and in this case even for the coefficient on teacher's dummy we do not reject zero effect, in spite of being quite similar in magnitude.

5.3 Schoolmates' Effect

A different exercise look at peer effects when a student has in her group what we call *schoolmates*. By *schoolmates* we mean students i and j of the same cohort that came from the same highschool.[3] Here we intend to understand if somebody who is potentially known since before getting into college affects the student in a way different from new classmates. For instance, Fletcher e Tienda (2009) find that having more colleagues coming from the same highschool is beneficial for performance of minorities in the University of Texas.

Table (5.4) below shows that in our data, there are few cases of groups with up to 3 students coming from the same school. More than 15% of the observations correspond to students in groups where he or she have at least one schoolmate.

Table 5.4: Schoolmates

No. Schoolmates	Freq.	Percent	Cum.
0	2,603	84.24	84.24
1	336	10.87	95.11
2	117	3.79	98.9
3	34	1.1	100
N	3,090	100	

In trying to estimate the impact of being on the leading teacher's group, we relied on an exogeneity argument. But here, differently, including a binary variable indicating the presence of a schoolmate would probably tell a story of selection. Only few of the best schools in São Paulo

[3] Changing the definition to include students from the same school but from other cohorts do not alter results significantly.

succeed in placing more than 1 student at FGV/EESP in the same year.[4] Thus, a binary variable indicating the presence of a schoolmate also indicate that the student probably went to a very good high school. So estimating a coefficient for such a variable is likely equivalent to estimating the correlation of achievement and good school background. However, since few schools place relatively many students we can adopt a strategy to look at how schoolmate's ability impact individual achievement, conditional on having a schoolmate. This is so because some students are more likely to have a schoolmate, but due to the assignment mechanism, variation in schoolmate's ability should be exogenous. Table (5.5) shows that indeed there is no correlation between student and schoolmates' ability.[5]

Table 5.5: Correlation Student and Schoolmate ability

	Student Math	Student Writing
Schoolmate	-0.240**	0.206*
	[0.119]	[0.117]
Writing	0.094	
	[0.071]	
Mathematics		0.109
		[0.090]
Observations	3485	3485

Dep. variable is student's own ability and regressors are dummy for schoolmate and schoolmates' mean ability. We run *writing* on *math* and vice-versa to avoid mechanical correlation.
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To do this exercise we run the following model:

$$y_{igct} = \alpha_0 + \alpha_1 \mathbf{x}_{igct} + \beta_1 S_{igct} + \alpha_2 (S_{gct} \times \breve{\mathbf{x}}_{igct}) + \alpha_3 \tilde{x}_{igct} + \varphi \mathbf{v}_{igct} + \varepsilon_{igct} \tag{5}$$

where S_{igct} is the variable binary indicating the presence of a schoolmate and $\breve{\mathbf{x}}_{igct}$ is a vector of schoolmates' mean ability measures. In this model, for students that have schoolmates in the group, peers' mean ability is divided between "new" and "old" peers. Again we are using as control variables income levels, fixed-effects for school, year, cohort, course and tutor. The results for this model are shown in table (5.6).

[4] Actually, more than one third of the students come from only 6 schools.

[5] Regression of writing on math and vice-versa tries to avoid the same mechanical correlation as in table (2.3).

Table 5.6: Schoolmate ability on Final Grade

	All periods	1st period	2nd period
Schoolmate	0.130**	0.189**	0.125
	[0.059]	[0.088]	[0.132]
Schoolmate			
Writing	0.113*	0.119	0.039
	[0.059]	[0.085]	[0.128]
Mathematics	-0.066	-0.104	-0.017
	[0.064]	[0.091]	[0.128]
Peers			
Writing	-0.109	-0.011	-0.032
	[0.078]	[0.121]	[0.189]
Mathematics	0.011	-0.018	0.104
	[0.067]	[0.120]	[0.183]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Consistent with the reasoning just exposed, the coefficient on the dummy variable is positive and statistically significant. It shows that having a schoolmate (or more probably, have gone to a very good school) is positively correlated with final grades, especially in the first period. Looking at schoolmates' mean ability, we see that having colleagues from the same school with better skills in writing is beneficial to performance in terms of final grades. The positive estimate may indicate that a "close friend" with good ability in writing could help a student in developing his arguments and ideas to be exposed in tutorial sessions. We see that the effect, though not statistically significant, is greater in the first period, when students would be more likely to look for support of known people. For "new" peers we do not reject zero impact, but coefficients are similar to estimates in tables (5.1) and (5.2).

We estimate the model using only schoolmates' mean ability (without "new" peers). Results are provided in the appendix and conclusions are very similar to what we just discussed. There could be correlation among the abilities of schoolmates, since they come from the same school and there could have been previous interaction. Thus, we run a model allowing for student fixed-effects to control constant unobservables potentially correlated with schoolmate's ability. Results are also in the appendix and conclusions are very similar.[6]

5.4 Nonlinearities

The linear-in-means model assumes that, if peer effects do exist, all students face the same impact no matter in the distribution of ability they are. This is somewhat restrictive. To departure from this environment we follow an specification similar to one proposed by Hoxby e Weingarth (2005). The idea is to check if students of different levels of ability are affected differently by peers across the ability distribution. According to the authors, this specification could explore different models of peer effects: (i) *Individual Comparison*: the presence of high achieving peers is harmful for performance; (ii) *Boutique/Tracking*: Students do better with peers similar to them; (iii) *Single Crossing*: Positive effect coming from high ability peers is weakly monotonically increasing in own

[6] In the appendix we also provide results for the following additional exercise: we modify equation (5) by using the interaction between indicator of schoolmate and peers' mean ability (instead of schoolmates' mean ability) and we add school fixed-effects interacted with peers' mean ability. This way we check if there is any difference in peers' impact for those who have a schoolmate (interaction of mate's indicator and peers' mean), but controlling for potential different impacts depending on school background (interaction with school FE). We find no evidence of peer effects in this specification.

ability.[7] We will show results for estimations based on the following equation:

$$y_{igct} = \sum_{m=1}^{3}\sum_{n=1}^{3} \pi_m^n (T_i^m \times P_i^n) + \varphi \mathbf{v}_{igct} + \varepsilon_{igct} \tag{6}$$

In this model, T_i^m is equal to 1 if student i is on the m-th tercile of the ability distribution and 0 otherwise. P_i^n is the proportion of i's peers on the n-th tercile of the ability distribution. Take for instance $T_i^1 = 1$. Then, π_1^3 is the coefficient on $T_i^1 \times P_i^3$ and gives the effect of an increase in the proportion of high ability peers in the group of a low ability student. Table (5.7) contains the estimated coefficients and standard errors for π_m^n, the impact on the performance of a student from the m-th tercile caused by an increase in the proportion of peers from the n-th tercile.

Table 5.7: Nonlinearities

	Math distribution			***Writing distribution***		
Student	Low	Mid	High	Low	Mid	High
Peers						
Low	0.303	0.441	0.704	0.536	0.578	0.750
	[0.497]	[0.496]	[0.594]	[0.480]	[0.556]	[0.569]
Mid	0.510	0.177	0.480	-0.149	0.386	0.493
	[0.563]	[0.486]	[0.613]	[0.570]	[0.544]	[0.590]
High	0.592	0.348	-0.225	0.362	0.419	0.645
	[0.542]	[0.541]	[0.523]	[0.566]	[0.607]	[0.542]
N	3010			3010		

Standard errors clustered by student in brackets
Control variables of model (5), table (3.3): own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Results are shown for equation (6) in two scenarios: the left panel shows estimates by dividing students according to ability in mathematics and in the right panel we use ability on writing. The interpretation is the the following: in the cell Low-High (row-column), for example, we see what would be the impact of raising the proportion of low ability peers for a high ability student i. The point estimate says that by adding 1 low ability peer in i's group[8] would make his performance

[7] Sacerdote (2011) tabulates several models of peer effects with a brief description for each one. Though, not all of them could be analyzed with the proposed econometric approach presented here.

[8] An average group of 12 students: 5 low, 4 mid and 3 high.

better by $0.704 \times 0.11 - (0.480 - 0.225) \times 0.08 = 0.06$ standard deviation.[9] However, all the estimates are not statistically significant. Qualitatively, it seems that diversity in math ability is better: the main diagonal contain the lowest effect for each type of student. Actually, increasing the proportion of students's same type would have a negative impact for all types.[10] Looking to results using students' ability distribution in writing (right panel), we also do not find statistically significant estimates. A qualitative analysis suggests that all types of students are not worse off if there is an increase in the proportion of low ability peers and low ability students are benefited from this. The picture emerging from these results suggests that diverse background in mathematics may promote ocasions for questions to be discussed from different points of views and this enhance performance, what would make us to reject the *Boutique Model*, in which students benefit from having similar peers. Besides, students with low ability in writing benefit from having peers with similar ability.

[9] The effect is calculated assuming a group increase from 12 to 13 students holding constant the number of mid and high ability peers.

[10] -0.05, -0.04 and -0.12 standard deviation for low, mid and high ability students, repsectively.

6 Conclusion

Our paper investigated peer effects in a selective higher education institution that adopted the *problem based learning* method. This environment provided the opportunity to observe groups of students for whom interaction is a core element for both learning and evaluation purposes. First, we used measures of peers' ability and characteristics in a basic linear-in-means specification to estimate peer effects on final grades. There was not any statistically significant estimate in these baseline results. Though, point estimates indicate negative impact of peers ability.

We then check if in groups conducted by the discipline's leading teacher there would be different results for peer effects. Again, we could not reject that peer effects are zero for both teacher's and other groups. This specification shows, however, that being in teacher's group is beneficial for student's performance. After that we tried to differentiate peers between people coming from student's same high school (schoolmates) and people coming from other high schools. We found positive and statistically significant results for the impact on students' performance of schoolmates' ability in writing. The estimate is about one third higher than what Carrell, Fullerton e West (2009) found, for instance. This results seems to come from interaction in their first period in college (though we do not reject the zero for estimates here), what suggests that when surrounded by many "new" colleagues, students look for somebody known in the available group.

Finally, we made an exercise departuring from the linear-in-means model. We analyze if students in different ranges of the ability distribution are affected differently by peers of different levels of ability. There is not statistically significant results at all. However, estimates suggest that all types of students do better in classes with students in all leves of math ability, i.e., tracking in math ability would not make them better. Besides, results suggest that students with low ability in writing benefit when they have a higher proportion of peers similar to them.

Concluding, we were able to find positive peer effects only when we look to former schoolmates, which constitute a subgroup of the exogenously assigned peers. Nonetheless, it does not mean that there is not peer effects coming from other people in the group. Although this is also a possibility, it is also likely that our data do not provide enough variation to allow identification through the econometric approaches used here. One possible way to extend the research is to develop some new allocation rule that increases variation of peers ability, as for example in the experiment of Booij, Leuven e Oosterbeek (2017). Some further alternatives are to compare students' performance (i) in groups formed according to the exogenous rule and in groups to which they self select; (ii) when they always have the same group and when the group varies;[1] and (iii) under some system of peer assessment.

[1]For example, half of the students have the same group of peers in all disciplines and half have different groups.

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A Tables

Table A.1: Peer Effects on Final Grade

	All periods	1st period	2nd period	All periods	1st period	2nd period	All periods	1st period	2nd period
Student									
Writing	0.169***	0.169***	0.148	0.172***	0.167***	0.149	0.168***	0.169***	0.141
	[0.051]	[0.053]	[0.097]	[0.050]	[0.053]	[0.096]	[0.050]	[0.053]	[0.098]
Mathematics	0.184***	0.197***	0.289***	0.186***	0.199***	0.284***	0.184***	0.197***	0.287***
	[0.055]	[0.071]	[0.098]	[0.056]	[0.072]	[0.098]	[0.056]	[0.071]	[0.098]
Female	0.309***	0.275**	0.389**	0.304***	0.286**	0.395**	0.306***	0.281**	0.401**
	[0.114]	[0.136]	[0.175]	[0.114]	[0.138]	[0.172]	[0.115]	[0.138]	[0.173]
Loan	0.111	0.209	0.006	0.117	0.213	0.038	0.121	0.208	0.037
	[0.150]	[0.249]	[0.309]	[0.149]	[0.250]	[0.307]	[0.149]	[0.249]	[0.315]
Peers									
Writing	-0.090	0.028	-0.022				-0.088	0.022	-0.098
	[0.080]	[0.124]	[0.193]				[0.082]	[0.124]	[0.199]
Mathematics	-0.019	-0.080	0.093				-0.032	-0.073	0.063
	[0.068]	[0.121]	[0.186]				[0.070]	[0.122]	[0.188]
Female				-0.124	0.139	0.211	-0.086	0.099	0.285
				[0.132]	[0.276]	[0.374]	[0.140]	[0.275]	[0.372]
Loan				0.240	0.049	0.416	0.283	0.033	0.429
				[0.226]	[0.397]	[0.609]	[0.224]	[0.398]	[0.618]
Observations	3010	1342	481	3010	1342	481	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))

Standard errors clustered by student shown in brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Peer Effects on First and Final Exam

	Final grade	1st Exam	Final grade
Student			
Writing	0.115***	0.176***	0.141***
	[0.038]	[0.049]	[0.054]
Mathematics	0.141***	0.227***	0.182***
	[0.045]	[0.059]	[0.060]
Female	0.211***	0.163*	0.284**
	[0.075]	[0.098]	[0.114]
Loan	0.076	0.203	-0.050
	[0.095]	[0.144]	[0.152]
Peers			
Writing	0.011	0.023	0.115
	[0.059]	[0.107]	[0.104]
Mathematics	-0.017	0.063	0.094
	[0.060]	[0.104]	[0.106]
Observations	2078	2078	2078

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Weighted Peer Effects on Final Grade

	All periods	1st period	2nd period
Student			
Writing	0.169***	0.167***	0.146
	[0.051]	[0.053]	[0.097]
Mathematics	0.183***	0.197***	0.283***
	[0.056]	[0.071]	[0.098]
Female	0.304***	0.274**	0.403**
	[0.115]	[0.138]	[0.174]
Loan	0.115	0.218	0.019
	[0.150]	[0.252]	[0.315]
Peers			
Female	-0.184	-0.066	0.444
	[0.202]	[0.371]	[0.567]
Loan	0.255	-0.069	0.258
	[0.284]	[0.503]	[0.794]
Writing	-0.131	-0.038	-0.062
	[0.107]	[0.162]	[0.307]
Mathematics	-0.051	-0.024	0.048
	[0.093]	[0.166]	[0.268]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Teacher Interaction: Student and Peers' ability

	All periods	1st period	2nd period
Student			
Writing	0.173***	0.190***	0.141
	[0.054]	[0.058]	[0.101]
Mathematics	0.211***	0.214***	0.271***
	[0.060]	[0.079]	[0.101]
Female	0.307***	0.270**	0.394**
	[0.114]	[0.136]	[0.178]
Loan	0.110	0.213	-0.019
	[0.150]	[0.251]	[0.310]
Teacher	0.080*	-0.041	0.042
	[0.046]	[0.109]	[0.178]
Teacher × Student			
Writing	0.001	-0.043	0.063
	[0.033]	[0.049]	[0.081]
Mathematics	-0.070**	-0.047	0.089
	[0.035]	[0.058]	[0.078]
Peers			
Writing	-0.076	0.140	0.078
	[0.099]	[0.168]	[0.306]
Mathematics	-0.089	-0.165	-0.013
	[0.094]	[0.165]	[0.201]
Teacher × Peers			
Writing	-0.018	-0.283	0.010
	[0.139]	[0.236]	[0.381]
Mathematics	0.148	0.251	0.661
	[0.146]	[0.241]	[0.622]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Teacher Interaction: Student and Peers' characteristics

	All periods	1st period	2nd period
Student			
Writing	0.172***	0.166***	0.148
	[0.050]	[0.053]	[0.097]
Mathematics	0.184***	0.196***	0.284***
	[0.056]	[0.072]	[0.098]
Female	0.289**	0.338**	0.395**
	[0.122]	[0.155]	[0.184]
Loan	0.085	0.261	0.083
	[0.154]	[0.305]	[0.315]
Teacher	0.071	0.163	0.161
	[0.135]	[0.242]	[0.541]
Teacher × Student			
Female	0.030	-0.136	0.018
	[0.072]	[0.122]	[0.166]
Loan	0.071	-0.058	-0.161
	[0.096]	[0.187]	[0.312]
Peers			
Female	-0.201	0.174	0.390
	[0.173]	[0.375]	[0.613]
Loan	0.415	0.592	0.607
	[0.275]	[0.587]	[0.701]
Teacher × Peers			
Female	0.138	-0.080	-0.287
	[0.252]	[0.517]	[0.751]
Loan	-0.361	-0.826	-0.577
	[0.381]	[0.647]	[1.874]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Schoolmate ability on Final Grade

	All periods	1st period	2nd period
Student			
Writing	0.182***	0.188***	0.147
	[0.051]	[0.054]	[0.099]
Mathematics	0.184***	0.189***	0.294***
	[0.056]	[0.072]	[0.097]
Female	0.304***	0.249*	0.389**
	[0.116]	[0.134]	[0.175]
Loan	0.092	0.147	0.016
	[0.144]	[0.238]	[0.311]
Schoolmate	0.130**	0.189**	0.125
	[0.059]	[0.088]	[0.132]
Schoolmate			
Writing	0.113*	0.119	0.039
	[0.059]	[0.085]	[0.128]
Mathematics	-0.066	-0.104	-0.017
	[0.064]	[0.091]	[0.128]
Peers			
Writing	-0.109	-0.011	-0.032
	[0.078]	[0.121]	[0.189]
Mathematics	0.011	-0.018	0.104
	[0.067]	[0.120]	[0.183]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Schoolmate ability on Final Grade

	All periods	1st period	2nd period
Student			
Writing	0.186***	0.188***	0.152
	[0.050]	[0.054]	[0.097]
Mathematics	0.185***	0.190***	0.289***
	[0.056]	[0.073]	[0.098]
Female	0.302***	0.250*	0.387**
	[0.115]	[0.134]	[0.175]
Loan	0.090	0.147	0.028
	[0.144]	[0.237]	[0.307]
Schoolmate	0.130**	0.190**	0.121
	[0.059]	[0.088]	[0.133]
Schoolmate			
Writing	0.116*	0.119	0.045
	[0.059]	[0.085]	[0.128]
Mathematics	-0.065	-0.104	-0.021
	[0.064]	[0.091]	[0.125]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Schoolmate ability on Final Grade - Student Fixed-Effects

	All periods	1st period	2nd period
Loan	0.163	1.056	-0.162
	[0.220]	[1.169]	[0.351]
Schoolmate	0.177***	0.194**	-0.009
	[0.053]	[0.081]	[0.115]
Schoolmate			
Writing	0.122**	0.085	0.056
	[0.047]	[0.065]	[0.108]
Mathematics	-0.038	-0.078	0.064
	[0.056]	[0.076]	[0.128]
Peers			
Writing	-0.096	0.010	-0.027
	[0.075]	[0.115]	[0.213]
Mathematics	0.069	0.069	0.101
	[0.068]	[0.129]	[0.202]
Observations	3021	1349	483

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Schoolmate Interaction

	All periods	1st period	2nd period
Student			
Writing	0.185***	0.178***	0.185
	[0.053]	[0.061]	[0.146]
Mathematics	0.174***	0.166**	0.302**
	[0.058]	[0.076]	[0.144]
Female	0.299***	0.227	0.380
	[0.114]	[0.145]	[0.239]
Loan	0.075	0.216	-0.081
	[0.155]	[0.253]	[0.423]
Schoolmate	0.151**	0.168	0.159
	[0.063]	[0.110]	[0.190]
Schoolmate $\times$ ***Peers***			
Writing	0.085	-0.021	0.475
	[0.218]	[0.382]	[0.635]
Mathematics	-0.097	-0.098	-0.816
	[0.206]	[0.366]	[0.681]
Observations	3010	1342	481

Dep. variable is final grade; control variables are own ability and characteristics, income levels, fixed-effects for school, year, cohort, course and tutor. (See model (5), table (3.3))
In this model we include an interaction between peers's mean ability and school fixed effects
Standard errors clustered by student shown in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Separating Endogenous and Contextual Effects

Here we follow the instrumental variable approach of Bramoullé, Djebbari e Fortin (2009) in an exercise to estimate endogenous and contextual peer effects separately by running

$$\mathbf{y} = \beta\mathbf{G}\mathbf{y} + \mathbf{X}\gamma + \mathbf{G}\mathbf{X}\delta + \varepsilon$$

where $\mathbf{G}$ computes peers' mean in each group for some measure of performance $\mathbf{y}$ and for relevant characteristics $\mathbf{x}$. The ideia is that with group size variation we could use $\mathbf{G^2X}$ as instrument for $\mathbf{Gy}$. Results are shown in tables (B.1) and (B.2). We see no significant estimates in the first stage and we do not reject that peer effects are zero in the second stage. These results would not support the condition $|\beta| < 1$, necessary for estimating the reduced form.

Table B.1: First Stage Results

	$\mathbf{Gy}$
$\mathbf{X}$	
Writing	-0.025
	[0.032]
Mathematics	0.014
	[0.036]
Loan	0.014
	[0.073]
Female	0.007
	[0.061]
$\mathbf{GX}$	
Writing	-0.110
	[0.335]
Math	0.321
	[0.373]
Loan	0.156
	[0.789]
Female	0.258
	[0.638]
$\mathbf{G^2X}$	
Writing	0.148
	[0.366]
Math	-0.236
	[0.407]
Loan	0.050
	[0.861]
Female	-0.104
	[0.699]
Observations	3186
F	6.525

Standard errors in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Second Stage Results

	y
Gy	
Endogenous	-4.309
	[7.535]
X	
Writing	0.100
	[0.087]
Mathematics	0.136**
	[0.069]
Loan	-0.003
	[0.110]
Female	0.118
	[0.131]
GX	
Writing	0.158
	[0.447]
Math	0.361
	[0.767]
Loan	0.348
	[0.472]
Female	0.084
	[0.436]
Observations	3186

Standard errors in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$