Peer Group Effects on the Academic Performance of Italian Students*

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Abstract. We analyse peer group effects among students of an Italian middle-sized public university. We explain students' average grade in exams passed during their Second Level Degree on the basis of pre-determined measures of abilities, personal characteristics and peer group abilities. Thanks to a rich administrative dataset we are able to build a variety of definitions of peer groups, describing different kinds of students' interactions, based on classes attended together or exams taken on the same session. Self-selection problems are handled through Two-Stage Least Squares estimation using as instrument the random assignment of students to different teaching classes in compulsory courses attended during their First Level degree. We find statistically significant peer group effects among students, which are robust to the different definitions of peer group and to different measures of abilities.

JEL Classification: I21; Z13; J24.

1. Introduction

Educational economists have highlighted through theoretical and empirical studies the relevance of peer group quality for student performance (Epple and Romano, 1998; Hoxby, 2003). Peer group affects student achievement in several different ways: members of a group interact in learning and help each other with work study, share important information, impose externalities on others by behaving well or badly (for example, a noisy student disrupts study environment), contribute to the formation of values and aspirations, and so on.

Understanding the nature and the size of peer group effects in education is crucial for the "productivity" of educational processes and the organizational design of school systems. For example, in order to improve student outcomes it is important to know which inputs mostly determine their performance and the relative importance of peer effects compared to other type of inputs, such as teachers quality or school resources. Peer effects are also key for school design. If peer effects are at work educational outcomes are affected by how students are arranged across classes and the desirability of comprehensive schools (which mix students of different abilities together) or stratified schools (which tend to aggregate students according to their abilities) depends on the magnitude and non-linearity of peer effects. Moreover, the nature

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of peer effects has important implications also for the attractiveness of school choice, which may favour sorting of students by abilities.

Starting from the classical study of Coleman *et al.* (1966), a host of works have analysed the effects of peer group on children's achievement and educational outcomes (Betts and Morell, 1999; Hoxby, 2001; Angrist and Lang, 2004; Hanushek *et al.*, 2003) and on college students' grades and choices of major (Sacerdote, 2001; Zimmerman, 2003; De Giorgi, Pellizzari and Redaelli, 2006; Foster, 2006), but several problems and controversies remain still open. Some of these studies shown that peer effects are statistically and economically significant in a variety of educational contexts and that students tend to realize better outcomes if their peer group quality is higher (Hoxby, 2000a; Zimmer and Toma, 2000; Sacerdote, 2001; Zimmerman 2003). Moreover, a number of these studies show that peer group effects are often non-linear, implying that students of middle abilities are particularly affected by the negative influence of worse students (Sacerdote, 2001; Zimmerman, 2003). However, the significance and size of peer effects often changes in relation to the sample used. Other studies find, in fact, no significant (or small) peer effects (Angrist and Lang, 2004; Arcidiacono and Nicholson, 2005; Foster, 2006).

Earlier analysis of peer effects were based on simple econometric models regressing students outcomes on their own individual characteristics (measures of ability, family background and so on) and on their peers' outcomes or characteristics.

As shown by Manski (1993), this kind of regressions are plagued by two main econometric problems, which raise doubts on the causal interpretation of the coefficient measuring peer group effects. The first problem, known as "self-selection" bias, depends on the fact that groups of peers are often not exogenously determined, but individuals typically choose people with whom to associate. Therefore, the characteristics of each student contribute to determine the choice of her peers and if some of these characteristics are not observable an endogeneity problem arise.

The second econometric trouble, known as "reflection" problem, emerges because the outcomes of students in a peer group evolve in an interdependent manner: the achievement of each member affects the achievement of other members but, at the same time, is affected by their achievement. Therefore, an estimation bias emerges, due to simultaneity and inverse causality.

Recent empirical studies have undertaken a variety of estimation strategies to handle these problems. A strategy used by a number of researchers is that of relying on some sort of natural experiment which determine random assignment of peers. Sacerdote (2001), Zimmerman (2003) and Foster (2006) analyse peer group effects among undergraduate students who are randomly assigned to college residence. Recently, De Giorgi, Pellizzari and Redaelli (2006) use random assignment in teaching classes as identification strategy to estimate peer effects in the choice of the major of study. Other works rely on instrumental variables to remove the correlation between unobserved characteristics and peer characteristics trying to find exogenous determinants of peer quality (Evans, Oates and Schwab, 1992; Case and Katz, 1992). A number of papers try to take into account the endogeneity of the peer group controlling for school and individual fixed effects (Arcidiacono and Nicholson, 2004; Hanushek, Kain, Markman and Rivkin, 2003).

Most of the works on peer effects among college students use data from (highly selective) US universities, whereas few works have analysed peer effects in European universities. Our analysis goes in the direction of reducing this gap by providing evidence on peer effects among students of a middle sized Italian university located in the South of the country. We use a rich administrative dataset of students enrolled at the Second Level Degree in Business and Economics at the University of Calabria and estimate peer effects using different definitions of peer group, mainly based on students attending classes together and sitting their exams on the same session. This approach is based on the observation that classmates contribute to shape educational environment and students typically interact and establish friendly relationships with students attending lectures in the same classes.

Our dataset provides us with very detailed information on exams. In their Second Level Degree students have the possibility to choose among a large number of different courses and, as a consequence, they take different exams. This allows us to define a first measure of peer group: for each student *i* we consider as members of her peer group those students who have taken courses together with *i*. Peer group quality is then calculated as the weighted average of abilities of students in the group, using as weights the number of courses taken together. We are also able to observe all students passing an exam on the same date. We use this information to define a second measure of peer group quality which weights the abilities of each student each student according to the number of exams taken together with student *i*.

We are aware that these definitions may be affected by self-selection problems since students choose others to connect with in studying. In order to overcome possible self-selection problems we use a Two-Stage Least Squares estimation and instrument peer groups through the random (and compulsory) assignment of students to different classrooms during their First Level degree.

Our estimations show that peer group abilities have a strong and positive effect on students’ academic performance. These effects are not led by self-selection and are robust to a variety of definitions of peer group and several measures of abilities.

The paper is organized in the following way. In section 2 data are presented and some descriptive statistics are offered. In section 3 we estimate a simple OLS model. In section 4 we instrument our measures of peer group using as instrument the random assignment of students to different teaching classes. Section 5 concludes.

2. Data and Descriptive Statistics

Our analysis is based on administrative data from University of Calabria, a middle-sized public university located in the South of Italy. It has currently about 27.000 students enrolled in different degrees and at different levels of the Italian University system, which, since 2001, is organized around three main levels, constituted by First Level degrees (3 years of legal duration), Second Level degrees (2 years) and Ph.D. degrees. Students who have accomplished a First Level degree can undertake a Second Level degree and after this they can enrol in a Ph.D degree.

We focus our analysis on students enrolled in years 2004-2005 and 2005-2006 at the Second Level degree in “Business Administration” (“Economia Aziendale”) and “Applied Economics” (“Economia Applicata”). The data we have at hand provide detailed information on the students’ university curricula (grades obtained in each course and date of each exam, gender, type of high school attended and high school final grade, grades obtained in the First Level degree, year of enrolment), while they do not provide much information on family characteristics (we have only information on the place of residence).

We start from a sample of 298 students, but we exclude students with less than 3 exams and, to make comparable students enrolled in different years, we consider only exams taken in the first year of their degree. Moreover, for some students information on some characteristics is missing. Our resulting sample is composed by 275 students. Moreover, since in some regressions we use information on the academic career of students who have accomplished their First Level Degree at University of Calabria, we lose some other observations and the sample results composed by 241 students.

Table 1 provides descriptive statistics for the sample of students we use.

During the first year of the Second Level degree our sample of students have passed a total number of 2120 exams, with an average of 10.45 exams for each student. The grade in each exam ranges between 19.66 and 30.6[1]. The *Average Grade* over the exams taken by each student is the measure of academic performance which we use as dependent variable. The mean of *Average Grade* is 26.93.

About sixty percent of students are female. 107 students are enrolled at their second year and 167 at their first. About 90% of them are enrolled in the Business Administration major and the remaining in the Applied Economics major. Students come mainly from two different types of High school: Lyceums (35%) and Technical Schools and Vocational School (65%). High school Final Grade (which we denote throughout the paper with *AbilityHS*) ranges from 60 to 100, with a mean of 88.46.

A large part of our sample students have accomplished their first level degree at the

[1] Normal grade ranges from 18 to 30, but we consider equal to 31 the grade “30 cum laude”.

University of Calabria. The average grade they obtained at exams during their First Level Degree (denoted with *AbilityFirst*) is 25.51. The First Degree Final Grade ranges from 88 to 111 and has a mean of 102.62.[2]

In order to define a single index of individual ability (denoted with *Ability*) we undertake a principal component analysis summarizing the different measures of ability we have available (*AbilityHS*, *AbilityFirst*, First Degree Final Grade, High School type). Principal component analysis creates linear combinations of the original variables that captures the greatest variance. We use only the first principal component.

Table 1. Descriptive statistics for the sample of students

Variables	**Mean**	**Std. Dev**	**Min.**	**Max.**	**Obs.**
Average Grade in exams	26.927	2.093	19.666	30.6	275
Number of exams passed	10.454	5.260	3	22	275
High School final grade (*AbilityHS*)	88.465	11.630	60	100	275
Average Grade in First Level exams (*AbilityFirst*)	25.512	1.739	21.68	29.47	264
First Level Degree Final Grade	102.619	6.867	84	111	273
Ability	-0.157	1.294	-3.204	2.349	241
Female	0.618	0.487	0	1	275
High School Type: Lyceum	0.349	0.477	0	1	275
Year of enrolment	1.392	0.489	1	2	275
Business Administration Major	0.8945		1	0	246
Course Size	23.133	12.069	2	52.25	275

♣: Grades in each course ranges from 18 to 30. Moreover, it exists "30 cum laude" (which we consider equal to 31). High School Final Grade ranges from 60 to 100.

3. Econometric Estimation of Peer Group Effects

We analyse the influence of peer groups on academic performance assuming that a student academic performance is determined by her own characteristics and by the performance and characteristics of her peers. Therefore, we start from the following simple model:

[1]
$$Y_i = \alpha + \beta X_i + \phi \overline{X}(P_i) + \gamma \overline{Y}(P_i) + \psi z(P_i) + \varepsilon_i$$

where Y_i is the outcome of student *i*, X_i is a vector of individual characteristics of *i* (measures of her ability, personal characteristics and family background), $\overline{X}(P_i)$ includes the average (predetermined) characteristics of P_i, the peer group of *i* ("contextual effects" in the definition of Manski, 1993) and $\overline{Y}(P_i)$ are the average outcomes of *i*'s peer group (Manski's "endogenous

[2] The First Level Degree Final Grade is calculated on the basis of the average grade obtained at exams. In our regressions, we prefer to use *AbilityFirst* because the Final Grade compresses variability (normally everyone with an average grade of 27.5 or more obtains the maximum final grade, 110).

effect"), $z(P_i)$ are common (unobservable) characteristics of the peer group ("correlated effects"), ε_i is an error term.

As mentioned previously this model faces two main problems: "reflection" and "selection" bias. As regards the "reflection" problem, that is, the fact that the achievement of student *i*, Y_i, is determined by the outcome of her peers $\overline{Y}(P_i)$, but simultaneously $\overline{Y}(P_i)$ is determined by Y_i, we follow the literature (see Sacerdote, 2001; Ammermueller and Pischke, 2006), and considering an equation symmetric to [1] for the outcome of each student *j* in the peer group of *i*, by substitution we obtain the following reduced form equation:

$$Y_i = \frac{\alpha(1+\gamma)}{(1-\gamma^2)} + \frac{(\beta+\gamma\phi)}{(1-\gamma^2)}X_i + \frac{(\phi+\gamma\beta)}{(1-\gamma^2)}X_j + \frac{((1+\gamma)\psi z + \gamma\varepsilon_j + \varepsilon_i)}{(1-\gamma^2)}$$

or, more simply:

[2] $$Y_i = \tilde{\alpha} + \tilde{\beta}X_i + \tilde{\phi}X_j + \tilde{\varepsilon}_i$$

Estimating equation [2], we are therefore unable to recover the structural parameter ϕ and γ and distinguish "endogenous" from "contextual" peer effects, but, in equation [2] we obtain the magnitude of "total peer effects" $\tilde{\phi}$, which may be unsatisfactory from a theoretical perspective but it is what matters from a policy point of view.

Another important problem, which may lead to a biased and inconsistent estimate of $\tilde{\phi}$ using OLS, is the endogeneity of $\overline{X}_j$, due to the fact that individuals typically select the people with whom to associate. This clearly contrasts with an ideal situation in which individuals are randomly assigned to different peer groups. If peers are selected according to individual' characteristics that affect her own attainment (but are unobservable to the researcher) we may end up considering as a peer effect something that instead depends on the individual's own attributes which are captured through her peer group quality.

This issue is particularly relevant for our analysis since our measures of peer group are based on students taking common courses and exams: students with similar characteristics are likely to choose the same courses or to sit an exam in the same session. We tackle this problem using as an instrumental variable for peer group quality the random assignment of students to teaching classes, which, we believe, influences peer group, but it is not correlated to the error term $\tilde{\varepsilon}_i$, and estimating with the classical Two-Stage Least Squares (Evans, Oates and Schwab, 1992).

We first estimate a single-equation model with Ordinary Least Squares (OLS) assuming that peer group quality is exogenous. In the next Section, we extend the model to deal with the endogeneity problem, treating peer group as a choice variable.

Our dependent variable Y_i is the *Average Grade* in exams taken by student *i* during their first year of Second Level Degree. In the vector X_i are considered, in turn, different measures of *i*'s own ability (High School Final Grade (*AbilityHS*); Average Grade in First Level Degree (*AbilityFirst*); a composite index of individual ability (*Ability*)). Other personal characteristics included in vector X_i are: a gender dummy (*Female*); a dummy for the type of High School (*Lyceum*); dummies for province of residence.

In order to take into account the level of difficulty of different courses chosen by each student (or different evaluation criteria used by lecturers),[3] we control in each regression for the average of grades (*Grade*) obtained by all other students taking a given exam and consider the average over all exams taken by student *i*.

In Table 2 we report estimates of alternative specifications of our model. In all specifications, standard errors (reported in parentheses) are corrected for heteroskedasticity. All equations include a constant and province of residence dummies (not reported to save space).

We first estimate an equation without peer effects to check which factors determine academic performance. In column (1), we see that *AbilityFirst* strongly explains our dependent variable, while *AbilityHS* is not significant.[4] The dummy *Female* and *Lyceum* are not significant, nor are the dummies for province of residence.

The other columns in Table 2 include peer group abilities as explanatory variables.

We use different measures of peer group. From a theoretical point of view it is not clear whether a student is influenced mainly by her close friends, or by her classmates, or by her roommates in college, or by people from her place of residence. Our definitions of peer group are at aggregate level and tend to describe different types of interactions among students.

Our first definition of peer group (*Peer Course*) is based on the group of students who have taken a given course, attending classes and taking the exam in the same academic year. Therefore, we are assuming that the relevant peer group is represented by people who attend classes together. As shown by Lazear (2001), education in a classroom environment is a public good. Weak students may impose negative externalities on other students by disturbing or slowing-down learning and viceversa.

Students at the Second Level degree in Business and Administration at the University of Calabria enrol in a wide range of courses. We do not observe directly the composition of students in each course but we infer this information from exams taken by students in a given year.

For each exam *k* taken by student *i*, we first determine the average ability (using different measures: *AbilityHS*, *AbilityFirst* and *Ability*) of all other students taking the same course. Then, we take the average over all the exams taken by *i* to calculate the ability of *i*'s peer group:

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[3] Students have a certain freedom to choose exams in their Degree program, after some compulsory courses.

[4] This is likely due to the high collinearity between *AbilityHS* and *AbilityFirst*. If we consider only *AbilityHS* as measure of ability, it results highly significant with a p-value of 0.00 (not reported).

$$Peer\_Course_i = \frac{1}{N_i}\sum_{k=1}^{N_i}\left(\frac{1}{J_k}\sum_{j=1}^{J_k}A_j\right)$$

where A_j is the ability of j, J_k is the number of peers in the exam k, N_i are the exams taken by i. The average number of exams taken by each students is 10.45[5], while the average number of students in each course is 22.13.

Columns (2), (3) and (4) uses respectively as a measure of peer ability A_j *AbilityHS*, *AbilityFirst* and *Ability*. Peer quality based on *AbilityHS* has mean 89.57, standard deviation is 2.68 and ranges from 80.74 to 97.17. Peer quality built with *AbilityFirst* has a range of 24.25-27.89, with a mean value of 25,59 and a standard deviation of 0.779. Finally, *Ability* ranges from -0.988 to 1.097, with a mean of -0.0158.

In all the specifications peer effects appear positive and significant: in the regression in which we consider *Ability* the peer effects coefficient is significant at 1-percent, whereas when we use *AbilityFirst* the coefficient is (almost) significant at 10-percent.

An increase in the (pre-determined) ability of peer group of student *i* (however measured) leads to an increase in the academic performance of *i*. For example, as shown in column (2) an increase in the ability of peer group of ten points in *AbilityHS* (about 1-standard deviation) leads to an increase in student outcome of about 0.8 (recall that the mean of the dependent variable is 26.92 and standard deviation is 2.09). The effect results higher when we measure peer group ability on the basis of the average grade in the First-Level degree (*AbilityFirst*) in column (3) or on the basis of our composite index of individual ability (*Ability*) (column 4), suggesting that the high school final grade may underestimate peer ability.

The other explanatory variables have approximately the same magnitude and significance as in column (1). Our variables explain more than 50% of total variability.

[5] We excluded students who have passed less than 3 exams.

Table 2. OLS regression estimates for academic achievement.
Dependent variable: Average Grade in Second Level Degree exams

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Average Grade First Level Degree	0.734*** (0.071)	0.683*** (0.073)	0.694*** (0.074)		0.680*** (0.073)	0.665*** (0.073)
High School Final Grade	0.014* (0.010)	0.017 (0.010)	0.016 (0.010)		0.019** (0.010)	0.016 (0.010)
Ability				0.920*** (0.080)		
Female	0.033 (0.195)	-0.005 (0.191	-0.001 (0.198)	-0.212 (0.202)	-0.023 (0.187)	-0.028 (0.190)
Lyceum	-.0113 (0.200)	-0.080 (0.197)	-0.084 (0.391)		-0.090 (0.195)	-0.097 (0.193)
Grade	0.836*** (0.112)	0.776*** (0.111)	0.823*** (0.111)	0.750*** (0.115)	0.753 (0.115)	0.745*** (0.11)
CHdegree					0.009 (0.008)	
Income					-0.039 (0.085)	
Unemployment Rate					-0.033* (0.018)	
Peer Course (AbilityHS)		0.086** (0.040)			0.080** (0.041)	
Peer Course (AbilityFirst)			0.55 (0.034)			
Peer Course (Ability)				0.634*** (0.230)		
Peer Course Top						0.232 (0.194)
Peer Course Bottom						-0.623** (0.247)
R^2	0.569	0.578	0.574	0.530	0.541	0.588
Observations	241	241	241	241	241	241

Notes: The dependent variable is the Average Grade in Second Level Degree exams. In all regression are included a constant and dummies for province of residence. Standard errors (corrected for heteroskedasticity) are reported in parentheses. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level.

Following Betts and Morell (1999), in column (5) we also verify if socio-economic characteristics of the community where students come from influence their performance. We introduce an indicator of educational level, measured as the percentage of people leaving in the area of residence of student i with a college or a high school degree (*CH_degree*), income in the community of residence (*Income*), the unemployment rate in the area (*Unemployment*).[6] The only socio-economic characteristic of the area of residence which seems to play a relevant role (statistically significant at 10 percent level) is the unemployment rate in the area. Estimates

[6] We do not consider differences among schools since all students in our sample accomplished their high school in public schools which differ from the program of study (Lyceums. Professional and vocational schools) but do not differ in terms of resources or teacher/pupil ratio, since the system is highly centralized and uniform.

show that students coming from high unemployment areas tend to have lower performance. This may be due to the fact that higher unemployment rates discourage students, who expect lower probabilities of finding a job once graduated, and reduce their effort in studying activities (for example Brunello and Winter-Ebmer, 2003, find that high unemployment rates reduce students incentives to graduate early) or high unemployment rate may represent a good proxy of poor local economic conditions.

We also investigate non-linearity in peer effects. We have created two dummy variables for whether or not peer group quality was in the top (*Peer Course Top*) or in the bottom 25 percent of the distribution (*Peer Course Bottom*), using *AbilityHS* as a measure of abilities. The middle 50 percent represents the omitted category. As shown in column (6) students are negatively affected by having a peer group of poor quality (statistically significant at 5-percent level), while it results a positive, but not statistically significant, effect from having a peer group with ability in the top of the distribution. Results do not change using different measures of ability.

OLS estimates in Table 2 assume that peer group quality is an exogenous variable. However, individuals typically choose with whom to associate and so peer quality is, to some extent, endogenous. Therefore we need to deal with this problem to measure consistently peer effects.

4. Instrumental Variable Estimations

In order to estimate consistently the relevance of peer effects, we need to find an exogenous determinant of peer group. At the same time, it is required that this variable does not influence academic performance directly. We believe that our second definition of peer group (*Peer Class*) has these characteristics.

Peer Class is based on the classes attended by students in the first years of in their First Level Degree. A large part of students in our sample were already enrolled at the University of Calabria for their First Level degree. Because of the high number of students enrolled in the First Level degree in Business Administration (about 600 students), for each compulsory course in the first two years they were assigned to three different teaching classes (Class 1, 2 and 3) on the basis of the initial of their name.[7] This variable is likely exogenous because students are required to attend lectures in their assigned teaching classes and since it is in the student's interest to respect the assignment, because final exams are defined autonomously by lecturers teaching in each class (notwithstanding common programs).

We believe that the repeated interactions taking place among students in these classes are relevant in defining their peer group even some years later during the Second Level degree.

[7] In the following estimates, we lose 29 observations relative to the students in Applied Economics who were not assigned to different classes during their First Level Degree.

Moreover, to control the belonging to a given class does not determine student's academic performance (except through its influence on the composition of peer group) we consider in our estimations characteristic of the lecturers teaching in each class that may affect students performance, such as research activity and seniority. We do not expect these factors to have much importance, since the effects of different lecturers' abilities should be captured, at least partly, by different grades in the First Level degree, that we control for in our estimations. A part from these factors, resources devoted to teaching are the same in the three classes and the same institutional structure was valid along the two years.

For each year we consider as peers all the students attending the same classes and calculate peer group ability as the average ability (using the usual measures of ability) of these students. This definition of peer group, *Peer Class*, is likely to determine the quality of peers at the Second Level degree because students typically associate with people who attend the same classes, make friends and tend to form stable groups and keep studying together in the following years.[8] Obviously, this aspect can be empirically tested and, as we show below, the coefficient of the instrumental variable *Peer Class* in the first-stage regressions is always highly significant.

In Table 3 we first report results from three different estimates of the reduced-form equation in which the dependent variable is regressed on all the exogenous variables and on the instrumental variable *Peer Class*: in column (1) we use as measure of peer ability *AbilityHS* , in column (2) we use *AbilityFirst* and finally in column (3) we measure ability with the comprehensive index *Ability*. *Peer Class* is highly significant in all the specifications, implying both that our instrumental variable is a strong determinant of the peer group quality and that peer group influences academic performance. Lecturers' seniority and research productivity, measured through the number of published articles in referred journals, are not statistically significant.

[8] On this see also De Giorgi, Pellizzari and Redaelli (2006).

Table 3. Reduced form equation estimates for academic achievement.
Dependent variable: Average Grade in Second Level Degree exams

Explanatory Variables	***(1)***	***(3)***	***(2)***
Average Grade First Level Degree	0.683*** (0.083)	0.684*** (0.083)	
High School Final Grade	0.013 (0.012)	0.013 (0.012)	
Ability			0.903*** (0.081)
Female	0.012 (0.204)	0.017 (0 .204)	-0.237 (0.211)
Lyceum	-0.0169 (0.213)	-0.021 (0.213)	
Grade	0.862*** (0.110)	0.860*** (0.110)	0.085** (0.119)
Peer Class (AbilityHS)	0.155** (0.079)		
Peer Class (AbilityFirst)		0.370** (0.186)	
Peer Class (Ability)			1.003*** (0.336)
Lecturers' seniority	0.006 (0.007)		0.001 (0.009)
Lecturers' publications	-0.008 (0.018)		-0.010 (0.015)
R^2	0.594	0.585	0.554
Observations	213	213	213

Notes: The dependent variable is the Average Grade in Second Level Degree. In all regression are included a constant and dummies for province of residence. Standard errors (corrected for heteroskedasticity) are reported in parentheses. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level.

Two-Stage Least Squares

In this section we estimate with Two-Stage Least Squares the model explaining academic performance using as instrument for peer group ability the variable *Peer Class*. Results are shown in Table 4. As above, the first three columns use respectively as a measure of peer ability *AbilityHS*, *AbilityFirst* and *Ability*.

Panel B of Table 4 shows results from First Stage regressions for different peer ability measures. In all the specifications it emerges that *Peer Class* strongly determines the quality of peer group. Moreover, peer group quality is also influenced by student's own abilities.

Panel A show Two Stage Least Squares estimations. *Peer Class* is always highly significant, regardless of how ability is measured. For example, in column (2) if peer group quality increases of 10 points then student's outcome increases of 0.74.

In general, the IV coefficients results higher than OLS coefficients. This suggests that measurement errors in the quality of peer group – which can bias towards zero our coefficient of interest – are likely to be more important than the problems of reverse causality.

Finally, we consider a further definition of peer group (*Peer Exam*) based on students who sit to an exam on the same date. In each academic year students have available 7 different dates to take a given exam. Anecdotal evidence suggests us that students that study together (a particularly meaningful definition of peer group) tend to take exams on the same date.

For each student in our sample, we can calculate how many times she meets with any other students at exams or, more precisely, how many times they passed an exam on the same date.[9] Students who meet more often at exams are presumably part of the same group. Therefore, we calculate the ability of the peer group as a weighted average of "matched" students' abilities (with the three measures *AbilityHS, AbilityFirst and Ability*), using as weights the number of matches at exams:

$$PeerExam_i = \frac{1}{M_i} \sum_{j=1}^{n_i} m_{ij} A_j$$

where A_j is the ability of student *j*, m_{ij} is the number of times student *i* met student *j* at exams, n_i is the number of students met by *i*, and $M_i = \sum_{j=1}^{n_i} m_{ij}$ is the total number of matches of *i*.

This measure of peer group ability weights the ability of each member of the peer group according to the number of exams taken together: students that are observed to sit exams together many times are given a higher weight, while those who match less frequently are weighted less.[10] A similar strategy to build peer group is followed by Bayer *et al.* (2004)[11] and De Giorgi, Pellizzari and Redaelli (2006).

Columns (4), (5) and (6) in Table 4 use *Peer Exam* calculated respectively with *AbilityHS*, *AbilityFirst* and *Ability* and instrument this variable (which we suspect to be endogenous) again with *Peer Class*.

Even with this new definition of peer group, the results show that (i) *Peer Class* determines the formation of peer group (as shown by the high significance of the relative coefficient in first stage regressions) and that (ii) peer group quality is an important determinant of student's academic performance (regardless of the way abilities are measured).

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[9] Unfortunately, we have available only data on passed exams, but no information when students fail exams.

[10] We also experimented with a measure of peer group which excludes from the peer group all students sitting together only once or twice (because this meetings could be due to pure chance). Results are similar to those reported.

[11] Bayer *et al.* (2004) examine peer effects in criminal behaviour and build peer group as a weighted average of peer's characteristic, using as weight the time spent by individuals together in the same prison.

Table 4. IV regressions of academic performance
Dependent variable: Average Grade in Second Level Degree exams

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A: Two-Stage Least Squares				
Average Grade First Level Degree	0.564***	0.620***	0.651***		0.621***	0.620***	
	(0.090)	(0.096)	(0.084)		(0.076)	(0.090)	
High School Final Grade	0.021	0.017	0.017		0.008	0.014	
	(0.012)	(0.012)	(0.011)		(0.011)	(0.011)	
Ability				0.859***			0.760***
				(0.083)			(0.101)
Female	-0.157	-0.073	-0.072	-0.272	0.006	0.018	-0.155
	(0.220)	(0.223)	(0.202)	(0.208)	(0.204)	(0.196)	(0.207)
Grade	0.691***	0.727***		0.741***	0.710 ***	0.837***	0.735***
	(0.118)	(0.119)		(0.113)	(0.113)	(0.109)	(0.111)
Lyceum	0.076		0.028		0.074	0.006	
	(0.215)		(0.206)		(0.201)	(0.199)	
Peer Course (AbilityHS)	0.233***	0.172**			0.295***		
	(0.084)	(0.090)			(0.109)		
Peer Course (AbilityFirst)			0.074 **			0.776**	
			(0.041)			(0.431)	
Peer Course (Ability)				1.016***			0.571***
				(0.314)			(0.206)
Lecturers' publications		-0.021					-0.007
		(0.016)					(0.015)
Lecturers' seniority		0.007					-0.004
		(0.009)					(0.009)
			Panel B: First Stage Regressions				
Average Grade First Level Degree	0.466***	0.368***	0.212***		0.178*	0.061***	
	(0.112)	(0.114)	(0.084)		(0.104)	(0.021)	
High School Final Grade	-0.029	-0.021	0.002		0.024	0.004	
	(0.017)	(0.017)	(0.013)		(0.016)	(0032)	
Ability				0.044***			0.251***
				(0.016)			(0.058)
Female	0.610	0.492	0.265	0.024	-0.073	-0.091	-0.144
	(0.336)	(0.335)	(0.244)	(0.044)	(0.313)	(0.062)	(0.158)
Grade	0.766	0.788	0.415	0.109	0.542	0.040	
	(0.167)	(0.163)	(0.121)	(0.022)	(0.156)	(0.031)	
Lyceum	-0.367	-0.211	-0.126		-0.284	0.016	0.205
	(0.320)	(0.314)	(0.231)		(0.297)	(0.059)	(0.080)
Peer Class (AbilityHS)	0.790***	0.900***			0.624***		
	(0.109)	(0.129)			(0.102)		
Peer Class (AbilityFirst)			4.128***			0.393***	
			(0.206)			(0.053)	
Peer Class (Ability)				0.929***			1.758***
				(0.063)			(0.253)
Lecturers publications		0.076***					-0.005
		(0.026)					(0.011)
Lecturers seniority		-0.009					0.009
		(0.014)					(0.006)
R^2	0.555	0.579	0.720	0.551	0.243	0.351	0.368
Observations	213	213	213	213	213	213	213

Notes: The dependent variable is the Average Grade in Second Level Degree exams. Panel A reports the Two-Stage Least Squares estimates, instrumenting for Peer Course using Peer Class; Panel B reports the corresponding first stage.. In all regressions are included a constant and dummies for province of residence. Standard errors (corrected for heteroskedasticity) are reported in parentheses. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level.

5. Concluding remarks

A large empirical literature shows that peer group quality has important effects on student's performance and, more in general, on individual's outcomes. Most of researches on peer group effects in education are based on US, whereas very few works examine European schools or universities.

To our knowledge, this paper is the first attempt to evaluate peer effects in an Italian university.[12] Moreover, whereas many papers study highly selective universities with rather homogeneous groups of students (see Sacerdote, 2001), the students we consider are not sorted through a selection process and are very heterogeneous in terms of abilities. This factor, which widens variability, is likely to increase peer effects.

We regress student's Average Grade in Second Level Degree on her own predetermined characteristics and abilities and on her peers' abilities. We use a variety of definitions of peer group – based on the courses taken together, on teaching classes attended in First Level Degree, on the date of exam and on community of residence – and use different measures of abilities (High School Final Grade, First Level Degree Grade, type of High School). It is likely that peer group defined both at level of classes attended and of exams taken together captures the relevant interactions among students.

To overcome reflection problem, one of the main econometric problems that affect peer effects estimates, we use pre-determinate variables for abilities, but renounce to distinguish the channels through which peer group influences student's outcome. From a policy point of view, this is not particularly detrimental.

The second econometric problem in estimating peer effects is endogeneity, in that individuals tend to choose the people with whom to associate. In order to solve the problem of endogeneity of peer group, following Evans, Oates and Schwab (1992) we estimate a model with Two-Stage Least Squares, using as instrument for peer group the teaching classes at which students were assigned in compulsory courses during their First Level Degree.

Our results show very clearly that peer effects are positive and rather large. Being part of a group with higher abilities increases considerably student's academic performance. Results are robust to all the different definitions of peer group and different measures of ability used.

Peer group effects appear also non-linear. In particular, weak students seem to affect negatively other students much more than the positive effects exercised by good students. We also find that socio-economic characteristics of the community where students come from (in particular the unemployment rate) influence their academic performance.

[12] De Giorgi, Pellizzari and Redaelli (2006) examine for a prestigious Italian university the influence of peer groups on the choice of majors, rather than on academic performance.

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