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# PEER EFFECTS IN HIGHER EDUCATION: DOES THE FIELD OF STUDY MATTER?

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# Peer Effects in Higher Education: Does the Field of Study Matter?*

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***Abstract***

*Does the peer effect vary with the field of study? Using data from a middle-sized public university located in Southern Italy and exploiting the random assignment of first year students to college accommodation, we find that roommate peer effects for freshmen enrolled in the Hard Sciences are positive and significantly larger than for freshmen enrolled in the Humanities and Social Sciences. We present a simple theoretical model which suggests that the uncovered differences between fields in the size of the peer effect could plausibly be generated by between-field variation in labor market returns, which affect optimal student effort.*

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## Introduction

Understanding the nature and importance of peer group effects in education is crucial for education policy. Peer effects are relevant for school choice, tracking, affirmative action, selective admissions and to understand the sources of school quality. Empirical research which seeks to estimate the existence, size and non-linearity of peer effects has run into several problems, including the self-selection, reflection and correlated effects described by Manski, 1993.

Following Sacerdote, 2001, and Zimmermann, 2003, a popular approach in this literature has been to investigate roommate peer effects, because in a number of universities and colleges the allocation of students to rooms can be argued to be conditionally random. A summary of the empirical literature to date is that the evidence in favor of roommate peer effects is limited, with several studies finding small or no effects (see Foster, 2006; Stinebrickner and Stinebrickner, 2006 and Whinston and Zimmermann, 2003, for an assessment of the empirical literature; Carrell, Malmstromm and West, 2008, Lyle, 2007 and Siegfried and Gleason, 2006, for recent contributions).

Most of these studies use U.S. data and focus either on highly selective or on less selective colleges. To our knowledge, none has addressed the question whether peer effects vary with the field of study[1]. Perhaps one reason for this lack of research is that in the U.S. most entering freshmen take a wide variety of courses across different disciplines toward a 4 – year liberal art degree, and many do not even choose a major until the second year. In some European countries including Italy, instead, the choice of major or field of study is taken at college entry and before allocation to residential accommodation.

The aim of this paper is to investigate whether peer effects exist and vary with the field of study, using data on residential roommates at the University of Calabria, a middle – sized Italian University. Our analysis is based on the idea that the "production function" associating peer contextual effects to own performance varies across fields. One can think of different reasons why such variation can occur, by arguing, for instance, that in the Hard Sciences, where there are more "right answers", it is easier

[1] Carrell, Fullerton and West, 2008, use U.S. data to investigate whether peer effects vary with the course taken (maths and science versus foreign language and physical education). They find larger peer effects in the former group of courses.

than in other disciplines to simply get those answers from roommates – especially if they belong to the same field of study – on homework problems and thereby bump up one's grade. Additionally, students in the Hard Sciences may be more apt to work in groups, or the types of courses they take may allow for more synergies than in the Humanities.

In this paper, we suggest an alternative mechanism, the provision of effort at college. Following the existing literature, we model individual college performance as a function of contextual effects – own and peer ability – and endogenous effects – peer college performance - but add to the latter individual effort, in line with the view that, as argued by Costrell, 1996, "..student time and effort are arguably the most important inputs to education, for given level of ability.." (p.956).

We show that, if students select effort to maximize their expected utility and labor market earnings vary with the field of study, as suggested by the empirical evidence, optimal effort varies by field. Since the marginal effect of peer ability on effort is increasing in the expected payoff to college major, a key implication of our model is that the peer effect is stronger in the fields of study associated to better economic payoffs[2].

We test whether peer effects vary across field of study using data on students who live on campus at a middle-sized Italian University, using the fact that in the Italian institutional setup students are required to choose their field of study prior to college entrance. First, we document that the allocation of students to rooms in the residential halls of the University of Calabria is conditionally random. Next, we show that peer effects are positive and statistically significant for students engaged in the Hard Sciences (Engineering, Maths and Natural Sciences) but not for students enrolled in the Humanities and Social Sciences. Moreover, the difference in the size of the peer effect between the former and the latter group of students is positive and statistically significant. Finally, there is some evidence – again in the Hard Sciences – that the intensity of peer effects is higher when the peer belongs to the same field of study.

When measured as a percentage of the own background ability effect, the roommate peer effect detected in our study for the students in the Hard Sciences is equal

[2] This economic mechanism has the interesting implication that the size of the peer effect is not invariant to labor market shocks affecting the college wage premium.

to 0.197, which is not small in a comparative perspective: Zimmermann, 2003, finds a value of 0.042; Winston and Zimmerman, 2003, estimate a relative peer effect in the range 0.098 to 0.172; Stinebrickner and Stinebrickner, 2006, find a value in the range 0.073 to 0.193.

Since the expected returns to college are higher for students in the Hard Sciences, these results are consistent with the model of endogenous effort choice presented in the paper. We hasten to stress, however, that alternative explanations are also possible. For instance, the uncovered differences in the intensity of peer effects could derive not from optimal effort choice but from variations across fields in the parameters regulating the generation of college performance: there may be more possibilities for synergies in math and science courses versus humanities course (see Carrell, Fullerton and West, 2008).

The paper is organized as follows. Section 1 introduces our model of effort at college and peer effects. Section 2 describes the transition from the model to the empirical specification. In Section 3 we describe the data and the mechanism assigning students to rooms in the residential halls. Finally, the presentation and discussion of our empirical results is in Section 4. Conclusions follow.

## 1. Optimal Educational Effort, Peer Effects and the Field of Study: The Model

Assume that students enrolled in a field of study – such as Engineering or Humanities - use the same technology for the production of college performance, and share the same cost of effort function. They differ in their personal characteristics, such as ability, and in the ability of their peer. In order to reduce the model to its bare essentials, let each student be matched with a single peer, who could belong to the same field of study (k=s) or to a different field (k=d). Further assume that there are only two fields, Engineering (f=e) and the Humanities (f=h). Finally imagine that college life lasts a single period.

In his influential study of social effects, Manski, 1993, distinguishes between endogenous effects, wherein the propensity of a student to behave in some way varies with the behavior of his peer, and contextual effects, wherein this propensity varies with the exogenous characteristics of his peer. Sacerdote, 2001, implements this approach to study roommate peer effects by assuming that student performance depends on own ability, peer ability – the contextual effect – and on peer performance – the endogenous effect.

We argue in this Section that Sacerdote's characterization – which has becomes rather common in this literature - fails to capture the important fact that individual performance is affected by effort. The effort augmented performance equation is

$$y_i = a_o{}^f + a_1{}^f e_i + a_2{}^f q_i + a_3{}^{fk} q_j + a_4{}^{fk} y_j \qquad \text{f=e,h; k=s,d} \qquad [1]$$

where $y_i$ is college performance of student *i*, a linear function of individual (exogenous) ability $q_i$, own effort $e_i$, roommate ability $q_j$ and peer performance $y_j$. Notice that we allow the parameters $a_3$ and $a_4$ to vary not only with the field of study $f$ but also with whether the field of the peer is different from the field of the individual. The reason is that we expect the scope for mutual influence on grades to be stronger when peers belong to the same field. Substituting $y_j$ in [1] and rearranging yields

$$y_i = \beta_o{}^{fk} + \beta_1{}^{fk} e_i + \beta_2{}^{fk} q_i + \beta_3{}^{fk} q_j + \beta_4{}^{fk} e_j \qquad \text{f=e,h; k=s,d} \qquad [2]$$

so that performance depends on own and peer ability and effort. When $\beta_1{}^{fk} = \beta_4{}^{fk} = 0$ the expression above corresponds to the reduced form specification used by Sacerdote, 2001. For the sake of convenience we shall call Equation [2] "the production function" of individual college performance, which associates individual performance to own and peer effort and ability, and allows the effect of each explanatory variable to vary with the field of study and with whether the peer belongs to the same field or not.

While ability is exogenously given, effort is subject to individual choice. By changing their effort at a cost, individuals can alter their probability of passing the required exams and graduate. Let $\theta_f$ be the field - specific standard required to graduate. Conditional on individual and peer ability, the higher the standard, the higher the effort required to meet it (see Costrell, 1994). Passing rather than failing exams depends also on a random event $\varepsilon$ (luck), which we assume to have a standard normal distribution $\varepsilon \approx N(0,1)$. Therefore, the individual probability of success $P$ is given by

$$P_i = \Pr(y_i \geq \theta_f) = 1 - \Phi(\theta_f - y_i) \qquad [3]$$

where $\Phi$ is for the standard normal distribution function.

In the event of success, students expect to earn wages $W$, which depend both on the accumulated human capital at college and on field – specific demand and supply conditions. We proxy accumulated skills with performance at school and assume that expected earnings are given by

$$W_{if} = \alpha_f E(y_i) \qquad [4]$$

where the factor of proportionality $\alpha_f$ varies with the field of study and reflects both relative demand and supply conditions and average performance in the field. To illustrate, the higher college performance of an engineer contributes positively to his earnings, but the intensity of the effect depends both on the demand and supply of engineers and on the mean performance of fellow graduates in the same field. We shall call the factor $\alpha_f$ "the field of study effect".

In the event of failure to graduate, students may end up in occupations which are quite different from the field they have enrolled in. We posit that their alternative income $B$ is a linear function of individual ability and set $B_i = bq_i$. While it seems plausible that the impact of ability on earnings is higher in the event of success than in the event of failure, we impose here the milder restriction that the percentage wage premium from graduation $\frac{W}{B} - 1$ is independent of individual ability. This is equivalent to assuming that $\alpha_f \beta_2^{fk} - b = 0$.

Individual utility is linear in income and convex in effort. Rational students choose effort to maximize expected utility $EU$, conditional on their ability and the ability of their peer[3]. We show in the Appendix that when students solve their optimal

[3] This characterization corresponds to the following sequence of events: first, students choose the field of study;

programs and their peers belong to the same field, individual college performance is given by

$$y_i = c^f + \left[ \beta_2{}^f + \beta_1{}^f \frac{\mu_1{}^f + \mu_2{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} + \beta_4{}^f \frac{\mu_2{}^f + \mu_1{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} \right] q_i$$
$$+ \left[ \beta_3{}^f + \beta_1{}^f \frac{\mu_2{}^f + \mu_1{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} + \beta_4{}^f \frac{\mu_1{}^f + \mu_2{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} \right] q_j \qquad \text{f=e,h} \quad [5]$$

where c is a field specific constant term and $\mu_j{}^f$ , j=1,..,3, depend on parameters $\beta_s{}^f$ , s=1,..,4 and are increasing in the field of study effect $\alpha^f$ . When peers belong to different fields – for instance the individual to Engineering and the peer to the Humanities, we get

$$y_i = c^e + \left[ \beta_2{}^e + \beta_1{}^e \frac{\mu_1{}^e + \mu_2{}^h \mu_3{}^e}{1-\mu_3{}^e \mu_3{}^h} + \beta_4{}^e \frac{\mu_2{}^h + \mu_1{}^e \mu_3{}^h}{1-\mu_3{}^e \mu_3{}^h} \right] q_i$$
$$+ \left[ \beta_3{}^e + \beta_1{}^e \frac{\mu_2{}^e + \mu_1{}^h \mu_3{}^e}{1-\mu_3{}^e \mu_3{}^h} + \beta_4{}^e \frac{\mu_1{}^h + \mu_2{}^e \mu_3{}^h}{1-\mu_3{}^e \mu_3{}^h} \right] q_j \qquad [6]$$

The two reduced forms [5]-[6] show that the impact of own and peer ability on individual performance can vary across fields of study either because the parameters of the production function in equation [2] vary or because of differences in the field of study effect $\alpha_f$ , which affects optimal effort at school and $\mu_j$. When individual performance and the field of study effect are complements in the generation of earnings – as assumed in Eq.[4] - the following propositions hold:

**Proposition 1**: The effect of individual ability on college performance is stronger when the student is enrolled in fields of study with higher labor market payoffs (higher $\alpha_f$ ).

second, they apply for accommodation in the halls of residence and if successful are assigned to a peer; third, they select their optimal effort. We discuss the choice of the field of study at the end of this section and the allocation to residential housing in the empirical section of the paper.

Proof: see Appendix.

**Proposition 2**: Independently of whether the peer belongs to the same field of study or not, the intensity of the peer effect is stronger when the student is enrolled in fields of study with higher labor market payoffs (higher $\alpha_f$ ).

Proof: see Appendix.

In our model, peer ability $q_j$ affects individual performance both directly and indirectly – by influencing peer performance and own and peer effort. While the direct effect and the effect on peer performance are independent of labor market payoffs, the indirect effect on effort is not, because higher expected payoffs increase the impact of higher peer ability on the marginal benefits of effort. We can also establish the following corollary

**Corollary 1**: When the peer belongs to a different field of study, the size of the peer effect is stronger when the field of study of the peer yields higher labor market payoffs.

Proof: see Appendix.

The discussion so far has ignored that students are not randomly allocated to fields of study. We can accommodate choice of field in the current setup by assuming a sequential decision mechanism: in the first step students who graduate from high school select the field of study they want to enroll in. Conditional on this choice, they select the optimal level of effort required to complete college education and graduate. In the case of two fields, let $EU_i^e$ and $EU_i^h$ be the expected utilities associated to Engineering and the Humanities, where we have appropriately replaced individual and peer effort with their optimal values, and define $v_i^e$ and $v_i^h$ as the unobserved taste for the two fields[4]. Further assume that the field - specific cost of enrolling is $C_i^f$ . Then individual *i* will select Engineering rather than the Humanities if

[4] By introducing the unobserved taste terms we allow the possibility that talented individuals can choose to enroll in the Humanities even though their expected utility net of costs C is higher in the field of Engineering.

$$EU_i^e - C_i^e + v_i^e \geq EU_i^h - C_i^h + v_i^h \qquad [7]$$

## 2. Transition to the Empirical Specification

The model presented in the previous section is based on a number of convenient simplifying assumptions, which allow us to focus on the essentials of the mechanism that we wish to illustrate. One such assumption is that college students spend a single year at college. In practice, however, college regular length is longer than one year, and students face a multi-period decision problem. Our model can be adapted to account for this by assuming that current and future performance are perfect substitutes – so that only their sum matters for total performance at college – and by redefining peer ability as the average ability of peers during the time spent at college. With no discounting, effort is constant over time.

Our empirical specification is based on equations [5] and [6], and is similar to the one implemented by Zimmerman (2003) and Sacerdote (2001), among others. We estimate

$$GPA_i = \gamma_0^{fk} + \gamma_1^{fk} ACA_i + \gamma_2^{fk} ACA_j + \gamma_3^{fk} X_i + \xi_i \qquad [8]$$

where *GPA* is college performance during the first year, *ACA* is a measure of individual and peer ability and *X* is a vector of controls, which include gender, residence and field of study dummies[5]. These dummies capture correlated effects, wherein students in the same group tend to behave similarly because they face similar institutional environments and have similar individual characteristics (see Soetevent, 2006). For instance, field of study dummies are used to proxy the between – field variation in curricula, grading standards and resources which influence individual performance.

The error term $\xi_i$ is likely to include many factors which affect performance but are omitted from the regressors. For instance, suppose that individual effort is equal to optimal effort plus an unobserved component. Since optimal effort is a function of own

[5] We employ the same notation used by Sacerdote, 2001, to ease comparisons.

and peer ability, this component enters in the error term but is orthogonal to our regressors by construction. Additional excluded factors are other potential peers, parental effects and the choice of fields discussed at the end of the theoretical section. As argued by Sacerdote, however, if peers are allocated randomly, the OLS estimate of the peer effect is consistent even in the presence of omitted variables which affect *GPA* (Sacerdote, 2001).

## 4. Data and the Assignment of Students to Rooms

We use administrative data covering students who live on campus at the University of Calabria. The University of Calabria is a middle-sized public university located in the South of Italy, which currently enrols about 33,000 students in six fields of study (Economics, Pharmacy and Nutritional Sciences, Engineering, Humanities, Math and Sciences and Political Science),[6] and was ranked second in the 2004 list of Italian public universities of similar size for the relative quality of its services, infrastructures, computerization and financial support to students[7]. The University of Calabria offers accommodation to nearly 2100 entitled students - close to one fifth of whom are freshmen (on average 460 each year, corresponding to almost 10% of all freshmen enrolled each year)[8]. There are 12 residence halls (blocks), divided in flats and rooms. Six of these halls are located on campus and the remaining six are outside campus, at a distance of 3 to 6 kilometers. The number of rooms in a hall ranges from 18 to 84, with an average of 43.

We match the records of the University Residential Office on accommodation in the halls of residence from 2001 to 2006 with the administrative files containing information on individual characteristics and academic outcomes – number of passed exams and grades obtained in each exam. Individual background characteristics include gender, the type of high school attended, the high school final grade and parental

[6] After the 2001 reform, Italian universities offer both first level degrees, which last three years, and advanced degrees (second level degrees), which last two more years. In this study we only consider freshmen enrolled in first level degrees, who typically share rooms with students enrolled in the same type of degree. Only 2% of the students in our sample have roommates enrolled in a second level degree.

[7] See the ranking at http://www.repubblica.it/speciale/2004/censis/classifiche/mediatenei.html

[8] Students in the halls of residence and the entire population of students enrolled at the University of Calabria are rather similar in terms of GPA, high school grades and gender balance. The average GPA and the average high school final grade of students enrolled at the University of Calabria from 2001 to 2006 are respectively 24 and 87 – very close to the values in our sample (24 and 86). The percentage of female students is the 55%,, compared to 65.8% in our sample.

economic conditions, captured by a synthetic administrative indicator called ISEE, which takes into account household income and wealth and the number of household components. To be admitted to the halls of residence, students must have a value of ISEE below 14K euros – at 2006 prices - and reside at least 40 kilometers from campus. Conditional on admission, we have information on housing assignment – the hall, the flat and the room. In 2006, 56.2 percent of hall residents were in double rooms, 38.4 in single rooms and the remaining 5.4 percent in triple rooms.

As in most of the relevant empirical literature, we restrict our attention to incoming freshmen, for whom we are confident that residence assignment is conditionally random[9]. The assignment mechanism is as follows: students applying for University residence are ranked by the Residential Office according to their economic conditions – measured by ISEE; starting with the students with the lowest ISEE, each eligible student is asked by the personnel of the Residential Office to select one of the halls of residence. The rooms in each hall are ordered with a progressive number. If a vacancy is available in the selected hall, the student is assigned to the room with a vacancy and the lowest progressive number. If there is no vacancy in the hall, the student is prompted to select another hall, and the iteration continues until convergence.[10] Assigned accommodation can only be changed after the first year, depending on availability.

Differently from the American colleges studied in the literature (see Sacerdote, 2001, and Zimmermann, 2003, among others), applicants are not required to fill any housing questionnaire. Therefore, places in rooms and flats are assigned to students of the same gender independently of personal preferences for smoking, music and else. Furthermore, a freshman can be assigned both to other freshmen and to senior students.

Since students are assigned sequentially to rooms according to their economic conditions, a potential outcome of the assignment process might be that students end up in pairs or groups characterized by similar economic conditions and by similar academic ability, which could happen if the latter is strongly correlated with the former[11]. We believe that the link between economic conditions and ability is rather weak in our data

[9] Older students can try to change the roommate they share with, depending on availability of alternative accommodation.
[10] We are not able to observe whether students have been assigned to their preferred hall.
[11] When we regress own ISEE on roommate ISEE and additional controls we find that the correlation is positive but statistically significant only for the students enrolled in the Social Sciences.

because of the endemic understatement of income and wealth in the South of Italy[12].

We identify the peer with the roommate. Whether this is the peer of "potential influence" is obviously an open question, as discussed in detail by Stinebrickner and Stinebrickner, 2006. It is certainly the definition used by the bulk of previous empirical research. Since the emphasis of this paper is on the interaction between peer effects and field of study, we prefer to adopt a definition of peers already implemented in the literature.

Our initial sample consists of 2687 freshmen with a residential place at the University Campus from year 2001 to 2006. We drop 675 observations corresponding to individuals assigned to single rooms and 589 additional observations because of missing values in one or more relevant variables. These freshmen are enrolled in six different fields, Economics, Pharmacy and Nutritional Sciences, Political Science, Engineering, Maths and Natural Sciences and Humanities. We drop from the sample those enrolled in Pharmacy because of the small number of observations[13]. Finally, to avoid ambiguities in determining whether peers belong to the same or to different fields, we exclude students who share their room with more than one peer – and peers belong to different fields – and end up with a final sample of 1228 first year students.

Our measure of student performance at college, or *GPA*, is the average grade earned in the exams passed during the first year at college. Since courses vary in their difficulty, we weight each grade with the number of credits assigned to the course, relative to total credits earned in the year. The variable *GPA* ranges between 18 – the minimum passing line – and 30. One objection to this measure is that students may trade-off quality (average grade) for quantity (the total number of credits earned). If this is the case, measured *GPA* does not fully capture individual performance in the first year. Notice, however, that the sample correlation between *GPA* and total number of credits in our sample is positive and equal to 0.456. Therefore, students with high *GPA* tend also to complete more credits. To check the robustness of our empirical findings we use as an alternative measure of performance the outcome of a principal component analysis which includes two factors, *GPA* and number of credits earned.

In this literature, pre-determined academic ability is based on the results of

[12] According to the National Statistical Institute, irregular labor in Calabria covers 31 percent of total labor, compared to a national average of 13.4. See ISTAT, 2004.
[13] Results – available from the authors upon request - are robust to the inclusion of these students.

standardized test scores, such as the SAT for the US. No such test is available in Italy before college entry. Furthermore, compared to the US, where secondary school is comprehensive, Italian students are tracked fairly early – at age 14 – into general and vocational tracks. Even though the final exit exam is national, the contents of the exam vary according to the type of secondary school. Tracking introduces important heterogeneity in the final grade attained at the time of high school graduation. In order to mitigate this problem, we use the outcomes of international cognitive tests - taken at age 15 and recently carried out by the OECD under the PISA project - as measures of the quality of secondary schools. We extract our measure of individual academic ability – which we call *ACA* for brevity – from a principal component analysis which includes two factors, the marks at graduation from secondary school and the standardized average test score in maths, reading, science and problem solving in each type of high school. Since most of the students enrolling at the University of Calabria are from the South of Italy, we use the standardized PISA 2003 test scores (see OECD, 2004) for this part of the country[14].

Peer ability is the roommate ability in the case of a double room, and the simple average of roommates' ability in the case of triple and larger rooms[15].Table 1 shows the descriptive statistics for our sample of students. Average academic ability *ACA* ranges between 69.23 and 100, with an average of 88.63. It is higher for students graduating from the more demanding general track (Lyceum) than for students completing the vocational track, in spite of the fact that typically only the best of the latter enroll in college, compared to the vast majority of graduates from Lyceum.

The distribution of students across fields is not even, with 31% enrolled in Economics, 29% in the Humanities, 21.9% in Engineering, 9.7% in Mathematics and Natural Sciences and the rest in the field of Political Science[16]. The gender balance across faculties is not even: almost 80% of the students enrolled in the Humanities and Political Science are female; this percentage falls to about 72% and 63% for students enrolled respectively in Economics and Mathematics and Natural Sciences and is equal to about 35% in Engineering.

[14] Bratti, Checchi and Filippin, 2007, present evidence on the territorial differences in PISA test scores across the North and the South of Italy.
[15] Peers can be freshmen, sophomores or senior students.
[16] In our sample roommates cannot influence the choice of major, which is selected before assignment to residential accommodation. See De Giorgi et al, 2006, for a case where such influence is possible.

Table 1 shows a stark contrast between *ACA* and *GPA* marks across fields: while Engineering freshmen have the highest average *ACA* but the lowest *GPA*, students in the Humanities have a relatively low *ACA* and the highest *GPA*, suggesting that standards are significantly higher in the former field of study[17]. Not reported in the table is the distribution of freshmen by type of roommate: it turns out that 39.5% of the students in our sample share accommodation only with roommates enrolled in the same field of study, while the remaining 60.5% share rooms with at least one student enrolled in a different field. These values are slightly higher that those expected from random assignment, which suggest that the probability that a student in a double room gets a roommate in the same field of study is 34 percent.

Table 1. Descriptive statistics

| *Variables* | Mean | Std Dev | Min. | Max. | Obs. |
|---|---|---|---|---|---|
| *Female* | 0.658 | | 0 | 1 | 1228 |
| *Female - Engineering* | 0.347 | | 0 | 1 | 259 |
| *Female - Mathematics and Natural Sciences* | 0.625 | | 0 | 1 | 120 |
| *Female - Economics* | 0.714 | | 0 | 1 | 361 |
| *Female - Political Science* | 0.795 | | 0 | 1 | 127 |
| *Female - Humanities* | 0.789 | | 0 | 1 | 361 |
| | | | | | |
| *ACA - average* | 88.632 | 6.72 | 69.23 | 100 | 1228 |
| *ACA - Lyceum* | 94.855 | 4.65 | 69.23 | 94.25 | 828 |
| *ACA - Technical/vocational* | 85.626 | 5.51 | 79.14 | 100 | 400 |
| *ACA - Engineering* | 90.787 | 7.26 | 69.23 | 100 | 259 |
| *ACA - Mathematics and Natural Sciences* | 89.500 | 7.86 | 69.61 | 100 | 120 |
| *ACA - Economics* | 87.679 | 5.99 | 69.23 | 100 | 380 |
| *ACA - Political Science* | 87.933 | 6.69 | 69.23 | 100 | 127 |
| *ACA - Humanities* | 87.997 | 6.16 | 69.23 | 100 | 361 |
| | | | | | |
| *GPA - average* | 24.186 | 2.78 | 18 | 30 | 1228 |
| *GPA - Engineering* | 22.509 | 2.63 | 18 | 29.82 | 259 |
| *GPA - Mathematics and Natural Sciences* | 23.836 | 2.50 | 18 | 29.68 | 120 |
| *GPA - Economics* | 23.385 | 2.45 | 18 | 29.3 | 361 |
| *GPA - Political Science* | 24.775 | 2.73 | 18 | 30 | 127 |
| *GPA - Humanities* | 26.099 | 2.12 | 18 | 30 | 361 |

The relatively small number of observations for Maths and Political Science and the similarities in the first year curricula suggest that we pool together Engineering and

[17] Engineering students have also the lowest number of credits completed during the first year.

Maths into the field of Hard Sciences, and Economics and Political Science into the field of Social Sciences[18]. By so doing, we end up with three different groups of fields: Hard Sciences, Social Sciences and Humanities. For each freshman, we classify a peer as belonging to the same field if he is enrolled in the same group of fields. Therefore, a roommate of an Engineering student is a peer of the same field if he is enrolled either in Engineering or in Maths and Natural Sciences, and of a different field if he is enrolled either in the Humanities or in the Social Sciences. In what follows, we shall use the word "field" to indicate the three groups, and "major" to indicate the majors included in each field. Hence, Engineering is a major and Hard Sciences a field.

To investigate the randomness of the assignment mechanism of students to residential halls, we follow the empirical literature and regress for each of the three fields of study individual ability *ACA* on peer ability and additional controls, which include a gender dummy, halls of residence and major dummies. If students were sorted into rooms by ability, the coefficient attracted by peer ability should be positive and statistically significant. Guryan, Kroft and Notowidigdo, 2007, show that regressions of own pre-treatment characteristics on peer pre-treatment characteristics have a small negative bias, and suggest controlling for mean ability of all potential peers, excluding own ability, as an effective way to remove the bias. Since the pool of potential peers in our data varies by cohort, we compute cohort–specific mean ability and include it in the all regressions presented in this paper, as prescribed by the authors.

Table 2 presents our estimates: in no case do we find evidence that own ability is correlated with roommate's ability, which suggests that allocation to rooms in our data is conditionally random[19]. Table 3 shows the estimated correlation between own and peer ability when we do not control for hall of residence dummies, use a larger sample which includes individuals with mixed peers, and separate freshmen according to whether their peers are in the same or in a different field. In the first row of the table we exclude halls of residence dummies from the set of controls, but fail to reject at the 5

[18] Compared to the U.S., where students generally take the same set of courses in the first year regardless of field of major, in Italy students enrolled in Engineering and the Humanities usually take completely different courses. Limited overlap can exist between Economics and Engineering or Maths, and between Political Science and the Humanities.

[19] Since the treatment is occurring at the room level, we cluster standard errors at this level to correct for serial correlation within rooms across time (Bertrand, Duflo and Mullainathan, 2004). We also bootstrap clustered standard errors (500 replications) to take into account that ACA is a generated regressor. Our empirical results do not change in a qualitative way if we perform separate regressions by major.

percent level of confidence the hypothesis that the conditional correlation between individual and peer ability is not statistically significant. Therefore, we conclude that the allocation of freshmen to rooms is conditionally random both within and between halls.

Table 2. Endogeneity checks. Dependent Variable: Own Ability (ACA). By field of study

| | *Hard Sciences* | *Social Sciences* | *Humanities* |
|---|---|---|---|
| *ACA Roommate* | 0.057 | -0.020 | -0.060 |
| | (.063) | (.051) | (.064) |
| *R-squared* | 0.131 | 0.044 | .096 |
| *Observations* | 378 | 488 | 362 |

Notes: bootstrapped and clustered standard errors within parentheses. Each regression include a gender dummy, halls of residence and major dummies, and the cohort specific mean ability of potential peers, net of own ability.

In the second row we use a slightly larger sample, which includes individuals with mixed roommates. In the third and fourth row, we test for randomness of the assignment by splitting the sample according to whether the peer is in the same or in a different field of study. In all these cases our qualitative results are unchanged. Finally, we regress a dummy variable for whether an individual's roommate is in the same field of study on own ACA. The results in the last row of the table show that the probability of getting someone in a particular field of study is uncorrelated with academic ability.

Table 3. Endogeneity checks. By field of study. Dependent Variable: Own ACA

| | *Hard Sciences* | *Social Sciences* | *Humanities* |
|---|---|---|---|
| *ACA Roommate – No Residence Dummies* | 0.081 | -0.013 | -0.051 |
| | (.063) | (.051) | (.060) |
| *ACA Roommate – Larger Sample* | 0.076 | -0.008 | -0.068 |
| | (.061) | (.049) | (.058) |
| *ACA Roommate – only Peers in Same Field* | 0.135 | -0.015 | -0.017 |
| | (.133) | (.104) | (.138) |
| *ACA Roommate – only Peers in Different Fields* | 0.029 | -0.007 | -0.081 |
| | (.075) | (.061) | (.076) |
| *Own ACA (Dependent variable: Peer in the Same Field)* | -0.004 | 0.004 | 0.005 |
| | (.004) | (.004) | (.004) |

Notes: see Table 2.

## 5. The Empirical Findings

### 5.1. *College Earnings, Academic Performance and the Field of Study*

Is there any evidence that college earnings include a field of study effect? Arcidiacono, 2004, uses data from the US National Longitudinal Survey of the Class of 1972 and finds large differences in earnings premia across majors even after controlling for selection, with returns being particularly high in the Natural Sciences and in Business. Similarly, Grogger and Eide, 1995, find that Science majors earn on average 32 percent more than high school graduates, while Humanities majors only earn a 10 percent premium.

We document the presence of a field of study effect in Italian earnings using data drawn from the 2001 wave of the Survey of college graduates in Italy (ISTAT, "*Indagine statistica sull'inserimento professionale dei laureati*"), which contains information on earnings three years after graduation plus a large array of controls, including the field of study, individual performance at college and before college, parental education and type of high school completed. Following Brunello and Cappellari, 2008, we regress log net monthly wages on individual performance, measured by final graduation marks relative to the within field mean, three dummies for the field of study (the Scientific group, which includes Maths, Sciences and Engineering; the Business group, which includes Economics, Political Science and Law; the Humanities, which includes also Linguistic and Pedagogical studies as well as Psychology; the remaining fields are in the constant term) and the following vector of observables: gender, region of employment, region of birth, labor market experience and type of job (part time versus full time), parental background in terms of occupation and education, year of birth, the actual duration of college studies, the type of high school attended (whether generalist or technical/professional) and the marks reported in the high school graduation exam. We also include interactions between parental education, high school type and graduation marks, combining two groups of variables at a time.

Conditional on the large set of observed individual characteristics, we assume that there is no residual correlation between college dummies and the error term, and that the relevant coefficients can be consistently estimated[20]. Our results in Table 4 show that graduating in a Hard Science (Maths, Sciences and Engineering) yields a 9.1 percent earnings premium (standard error: .007) with respect to graduating in Business, and a 14.2 percent gain (standard error: .010) with respect to graduating in the Humanities. This evidence confirms the findings based on US data that Science majors pay a substantial premium with respect to the Humanities[21].

Table 4. The Impact of the Field of Study on Earnings. Dependent Variable: log net monthly earnings

| | |
|---|---|
| *Scientific Fields Dummy* | 0.103*** |
| | (.010) |
| *Humanities Dummy* | -0.039*** |
| | (.012) |
| *Business Fields Dummy* | 0.012 |
| | (.011) |
| | |
| *R-squared* | 0.38 |
| *Observations* | 10420 |

Notes: the data are from ISTAT (2001). Robust standard errors in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 percent level of confidence respectively. The regression includes final graduation marks, gender, region of employment, region of birth, labor market experience and type of job, parental background in terms of occupation and education, year of birth, the duration of college studies, the type of high school attended (whether generalist or technical/professional), the marks reported in the high school graduation exam, interactions between parental education, high school marks and types.

### 5.2. *Peer Effects and the Field of Study*

According to the model discussed in Section 1, and in particular to equations [5] and [6], eventual between – field differences in the peer effect can be attributed either to differences in the field – specific production functions (the βs of equation [2]) or to the incentive effects associated to between – field variation in labor market payoffs – which influence the μs in [5] and [6] - or to both.

We estimate equation [8] for each of the three fields of study without distinguishing whether the peer belongs to the same or to other fields, and present our results in Table 5. In each regression we control for halls of residence and major effects, the average ability of potential peers and own ISEE. We find that the effect of own

[20] Clearly, the validity of such assumption depends on how well we control for factors that are related to individual ability and that may influence college choice. While there is no guarantee that our assumption is going to be met, we stress that the vector of observables consists of a detailed list of control factors, including interactions, which leads us to believe that omitted variables bias – if existent – is mild.

[21] Buonanno and Pozzoli, 2007, find similar results using propensity scores to control for the self-selection of students into fields of study.

ability on performance is positive and statistically significant in all fields, and highest in the Hard Sciences. More interesting for the purposes of this paper, we also find that peer ability has a positive and statistically significant effect in the Hard Sciences, and a negative but not significant effect in the other fields[22].

Table 5. Peer Effects. Dependent Variable: Individual GPA.

| | Hard Sciences | Social Sciences | Humanities |
|---|---|---|---|
| *Individual ACA* | 0.203*** | 0.189*** | 0.134*** |
| | (.016) | (.016) | (.020) |
| *Roommate ACA* | 0.040** | -0.008 | -0.026 |
| | (.017) | (.016) | (.017) |
| *Female* | -0.538** | 0.112 | -0.822*** |
| | (.246) | (.236) | (.287) |
| *Observations* | 378 | 488 | 362 |
| *R-squared* | 0.40 | 0.27 | 0.21 |

Note: see Table 2. Each regression includes halls dummies, sub-field dummies, individual ISEE, and the cohort average ability of potential peers. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 percent level of confidence respectively.

We test whether the size of the peer effect differs significantly between the Hard Sciences, Social Sciences and Humanities by pooling data and by interacting own and peer measured ability with the dummy *SOC*, equal to 1 if the freshman is enrolled in the Social Sciences, and with the dummy *HUM*, equal to 1 if the freshman's field is Humanities.[23] The results in column (1) of Table 6 confirm that peer ability has a positive and statistically significant effect on individual performance only for freshmen enrolled in the Hard Sciences. There is also evidence that the size of peer effects is significantly smaller in the Humanities and in the Social Sciences than in the Hard Sciences.

Columns (2) and (3) of Table 6 report the estimates when we separate freshmen depending on whether their peers are in the same or in another field. In either case, the statistically significant difference in the intensity of the peer effect in favor of the students enrolled in the Hard Sciences is confirmed. A comparison of the estimates in

[22] We also find that female students perform less well than males in Hard Sciences and the Humanities. The qualitative results in Table 5 are confirmed if we include in the data the students with mixed field roommates, who have multiple roommates engaged in different fields. Results are available from the authors upon request

[23] We also interact the gender dummy and own ISEE. Preliminary regressions cannot reject the hypothesis that additional interactions are jointly equal to zero.

the two columns shows that students in the Hard Sciences face stronger peer effects when peers belong to the same field than when they are in different fields (0.064 versus 0.033), in line with the predictions of our model. Results are less clear-cut in the case of the Social Sciences and Humanities, both because estimated peer effects are not statistically significant and because peers in different fields could be either in the Hard or in the Soft Sciences[24].

Table 6. Peer Effects. Dependent Variable: Individual GPA.

| | *Full Sample* | *Only Peers in the Same Field* | *Only Peers in Different Fields* |
|---|---|---|---|
| *Individual ACA* | 0.203*** | 0.207*** | 0.195*** |
| | (.016) | (.024) | (.023) |
| *Individual ACA * SOC* | -0.018 | -0.035 | -0.003 |
| | (.023) | (.040) | (.031) |
| *Individual ACA * HUM* | -0.071*** | -0.061 | -0.074** |
| | (.025) | (.037) | (.036) |
| *Roommate ACA* | 0.042** | 0.064** | 0.033 |
| | (.016) | (.029) | (.022) |
| *Roommate ACA *SOC* | -0.051** | -0.055 | -0.058* |
| | (.022) | (.040) | (.030) |
| *Roommate ACA * HUM* | -0.070*** | -0.106*** | -0.057* |
| | (.025) | (.041) | (.031) |
| *Female* | -0.600** | -1.256*** | -0.376 |
| | (.256) | (.442) | (.328) |
| *Female*SOC* | 0.743** | 1.799*** | 0.330 |
| | (.356) | (.633) | (.421) |
| *Female*HUM* | -0.194 | 0.677 | -0.456 |
| | (.401) | (.784) | (.453) |
| *Observations* | 1228 | 485 | 743 |
| *R-squared* | 0.44 | 0.46 | 0.44 |

Note: see Table 5

## 5.3. Robustness Checks

Since many freshmen share room with senior students, one wonders whether peer effects differ across the age of the roommate. We start by asking whether assignment to a senior roommate is random by regressing a dummy for senior peer on own ACA: in none of the three fields the association between these two variables is

[24] For a student in the Humanities, a peer in a different field can be in Engineering or in the Social Sciences.

statistically significant. Next, we investigate whether the coefficient associated to the roommate's ACA varies with the peer being a freshman or a senior student. As shown in Table 7, the impact of the peer's measured ability on individual GPA does not vary in a statistically significant way with roommate age.

Table 7. Peer Effects. Dependent Variable: Individual GPA.

| | Hard Sciences | Social Sciences | Humanities |
|---|---|---|---|
| *Individual ACA* | 0.203*** | 0.187*** | 0.138*** |
| | (.017) | (.018) | (.020) |
| *Roommate ACA – freshman* | 0.040** | -0.006 | -0.018 |
| | (.017) | (.018) | (.019) |
| *Roommate ACA – senior* | 0.038** | -0.009 | -0.022 |
| | (-.017) | (.018) | (.019) |
| *Female* | -0.608** | 0.041 | -1.047*** |
| | (.266) | (.262) | (0.319) |
| *Observations* | 378 | 488 | 362 |
| *R-squared* | 0.44 | 0.30 | 0.28 |

Note: see Table 5.

As shown in Table 1, the percentage of females students in the Hard Sciences is much lower than in the other fields. It is therefore possible that the uncovered differences in peer effects across fields reflect gender differences in the strength of these effects rather than variations in expected market returns from a college major. To check this, we replicate our estimates for the sub-sample of male freshmen and present our findings in Table 8. It turns out that our key results still hold, suggesting that they are not driven by gender differences in peer effects.

We have controlled for within – field differences in curricula and grading practices across disciplines with major dummies. In Italy, however, both curricula and grading standards can vary within each major, which is often organized in a number of courses of study. For instance, the major of Engineering may comprise courses in Civil, Chemical, Electronic and Mechanical Engineering. While these courses share the same core curriculum, several optional exams are course – specific[25]. To allow for these differences, we re-run our regression in the first column of Table 6 after replacing the major dummies with course of study dummies. As shown in the first column of Table A.1 in the Appendix, our key qualitative results are unchanged.

[25] Compared to courses of study, fields of study can have very different core curricula.

Table 8. Peer Effects. Dependent Variable: Individual GPA. Males only

| | Full Sample | Only Peers in the Same Field | Only Peers in Different Fields |
|---|---|---|---|
| *Individual ACA* | 0.209*** | 0.212*** | 0.196*** |
| | (.022) | (.031) | (.034) |
| *Individual ACA * SOC* | 0.018 | -0.018 | 0.026 |
| | (.036) | (.072) | (.053) |
| *Individual ACA * HUM* | -0.122*** | -0.015 | -0.138** |
| | (.043) | (.417) | (.057) |
| *Roommate ACA* | 0.051** | 0.078** | 0.023 |
| | (.021) | (.035) | (.026) |
| *Roommate ACA *SOC* | -0.097*** | -0.151** | -0.076* |
| | (.035) | (.072) | (.044) |
| *Roommate ACA * HUM* | -0.118** | -0.065 | -0.116** |
| | (.050) | (.022) | (.059) |
| *Observations* | 419 | 162 | 257 |
| *R-squared* | 0.47 | 0.49 | 0.52 |

Note: see Table 5

Next, as a further robustness check, we replace the dependent variable with the factor extracted from a principal component analysis which includes average GPA as well as total credits. Since the correlation of the latter with the former is positive and high (0.853), we are not surprised to find that such change has no significant qualitative effects on our results – see column (2) of Table A1).

## 6. Conclusions

The existing literature on peer effects in higher education has produced mixed evidence at best. Particularly detrimental to an adequate understanding of the phenomenon – which has many relevant policy implications – is that the economic and social mechanisms producing peer effects are far from clear. Using administrative data from University of Calabria, a middle-sized public University in Southern Italy, we have investigated whether roommate peer effects vary significantly with the field of study.

We have exploited the random assignment of first year students to college accommodation and found evidence that peer effects are positive and statistically significant for students enrolled in Engineering, Maths and Natural Sciences, and close to zero or negative but rather imprecisely estimated in the Humanities and Social Sciences. The non-linearity in the peer effect uncovered in this study offers potential insight to why many previous college peer effects studies have found little evidence of strong positive peer effects among college roommates.

We have presented a simple theoretical model which suggests that the uncovered differences between fields in the size of the peer effect could be generated by the between – field variation in labor market returns, which affect optimal student effort. While we believe that our explanation is plausible, alternatives cannot be excluded with the data at hand. For instance, between – field differences in the intensity of peer effects could derive not from optimal effort choice but from variations across fields in the parameters regulating college performance. An interesting implication of our model is that the size of the peer effect is not invariant to labor market shocks affecting the college wage premium.

## *Appendix*

### The Model

Individual utility $U$ is linear in income $I$ and convex in effort: $U_i = I_i - \frac{\psi e_i^2}{2}$. Disregarding non-labor income and the non-pecuniary costs and benefits associated to college life, expected utility is

$$EU_i = P_i \alpha_f E(y_i) + (1 - P_i) b q_i - \frac{\psi e_i^2}{2} \qquad [A.1]$$

The first order condition associated to the maximization of expected utility is:

$$P_i \alpha_f \beta_1^{fk} + \alpha_f E(y_i) \beta_1^{fk} \phi(.) - \beta_1^{fk} \phi(.) b q_i - \psi e_i = 0 \qquad [A.2]$$

where $\phi(.)$ is the density function of the noise term $\varepsilon$.

In order to study how individual effort varies when peer ability is marginally increased, it is useful to adopt the following first order Taylor approximations of the normal distribution and density functions around their mean

$$\Phi = \frac{1}{2} + f(0)\left[\theta_f - E(y_i)\right]$$

$$f = f(0) \qquad [A.3]$$

Using [A.3] in [A.2] we can re-write the first order condition as follows:

$$\left(\frac{1}{2} - f(0)\left[\theta_f - E(y_i)\right]\right)\alpha_f \beta_1^{fk} + \left[\alpha_f E(y_i) - b q_i\right]\beta_1^{fk} f(0) - \psi e_i = 0 \qquad [A.4]$$

where the second order conditions require that $\Delta_{fk} = \psi - 2\alpha_f \left(\beta_1^{fk}\right)^2 \phi(0) > 0$.

It is useful to distinguish two cases: a) the student and his peer belongs to the same field of study; b) the two belong to different fields. In the former case, we can use [A.4] to obtain two reaction functions with the same coefficients

$$e_i = \mu_o^f + \mu_1^f q_i + \mu_2^f q_j + \mu_3^f e_j \qquad \text{f=e,h} \qquad [A.5]$$

$$e_j = \mu_o^f + \mu_1^f q_j + \mu_2^f q_i + \mu_3^f e_i \qquad \text{f=e,h} \qquad [A.6]$$

where $\mu_o^f$ is a field – specific constant term[26] and

$$\mu_1^f = \frac{f(0)\beta_1^f \left(2\alpha_f \beta_2^f - b\right)}{\Delta_f} \qquad \mu_2^f = \frac{f(0)\beta_1^f \left(2\alpha_f \beta_3^f\right)}{\Delta_f}$$

$$\mu_3^f = \frac{f(0)\beta_1^f \left(2\alpha_f \beta_4^f\right)}{\Delta_f}$$

The pair [A.5] – [A.6] can be solved to yield the pair of optimal effort functions $e_i^*$ and $e_j^*$, which can then be replaced in Eq. [2] in the text to obtain the reduced form relationship between individual performance and own and peer ability (Eq. [5]).

In the case of individuals and peers belonging to different fields, assume for convenience that the individual is enrolled in Engineering and the peer in the Humanities. Then the two reaction functions are

$$e_i = \mu_o^e + \mu_1^e q_i + \mu_2^e q_j + \mu_3^e e_j \qquad [A.7]$$

$$e_j = \mu_o^h + \mu_1^h q_j + \mu_2^h q_i + \mu_3^h e_i \qquad [A.8]$$

and Eq. [6] obtains.

QED

[26] Since the pair of individuals belongs to the same field of study, we can drop the second index k.

*Proof of Propositions 1 and 2 and Corollary 1.*

Consider first the case where both members of the peer group belong to the same field of study. In this case we can use the pair of equations [A.5]-[A.6] to obtain

$$e_i^* = A_i{}^f + \frac{\mu_1{}^f + \mu_2{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} q_i + \frac{\mu_2{}^f + \mu_1{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} q_j$$

$$e_j^* = A_j{}^f + \frac{\mu_1{}^f + \mu_2{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} q_j + \frac{\mu_2{}^f + \mu_1{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} q_i$$

where $A$ is a suitable constant term, $i$ is the individual and $j$ his peer. Replacing these expressions into [2] and taking derivatives we obtain

$$\frac{\partial y_i}{\partial q_j} = \beta_3{}^f + \beta_1{}^f \frac{\mu_2{}^f + \mu_1{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} + \beta_4{}^f \frac{\mu_1{}^f + \mu_2{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} \qquad \text{f=e,h}$$

Since $\frac{\partial \mu_j}{\partial \alpha^f} > 0$ we obtain

$$\frac{\partial}{\partial \alpha^f}\left(\frac{\partial y_i}{\partial q_j}\right) > 0$$

We also have

$$\frac{\partial y_i}{\partial q_i} = \beta_2{}^f + \beta_1{}^f \frac{\mu_1{}^f + \mu_2{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2} + \beta_4{}^f \frac{\mu_2{}^f + \mu_1{}^f \mu_3{}^f}{1-\left(\mu_3{}^f\right)^2}$$

and the same result applies.

Next consider the case when the individual and his peer belong to different fields of study. To illustrate, let the individual be enrolled in engineering (e) and the peer in the humanities (h). Then we can use [A.7]-[A.8] to get

$$e_i^* = A_i^e + \frac{\mu_1^e + \mu_2^h \mu_3^e}{1-\mu_3^e \mu_3^h} q_i + \frac{\mu_2^e + \mu_1^h \mu_3^e}{1-\mu_3^e \mu_3^h} q_j$$

$$e_j^* = A_j^h + \frac{\mu_1^h + \mu_2^e \mu_3^h}{1-\mu_3^e \mu_3^h} q_j + \frac{\mu_2^h + \mu_1^e \mu_3^h}{1-\mu_3^e \mu_3^h} q_i$$

and we obtain for individual i

$$\frac{\partial y_i}{\partial q_j} = \beta_3^e + \beta_1^e \frac{\mu_2^e + \mu_1^h \mu_3^e}{1-\mu_3^e \mu_3^h} + \beta_4^e \frac{\mu_1^h + \mu_2^e \mu_3^h}{1-\mu_3^e \mu_3^h}$$

$$\frac{\partial y_i}{\partial q_i} = \beta_2^e + \beta_1^e \frac{\mu_1^e + \mu_2^h \mu_3^e}{1-\mu_3^e \mu_3^h} + \beta_4^e \frac{\mu_2^h + \mu_1^e \mu_3^h}{1-\mu_3^e \mu_3^h}$$

It is immediate to check that

$$\frac{\partial}{\partial \alpha^e}\left(\frac{\partial y_i}{\partial q_j}\right) > 0 \qquad \text{and} \qquad \frac{\partial}{\partial \alpha^h}\left(\frac{\partial y_i}{\partial q_j}\right) > 0$$

QED

Table A1. Peer Effects. Dependent Variable: Individual GPA. Robustness checks

| | *With Course of Study Dummies* | *With a Different Definition of the Dependent variable* |
|---|---|---|
| *Individual ACA* | 0.204*** | 0.116*** |
| | (.017) | (.007) |
| *Individual ACA * SOC* | -0.012 | -0.027*** |
| | (.023) | (.010) |
| *Individual ACA * HUM* | -0.066** | -0.057*** |
| | (.026) | (.011) |
| *Roommate ACA* | 0.034** | 0.015** |
| | (.016) | (.007) |
| *Roommate ACA*SOC* | -0.047** | -0.022** |
| | (.022) | (.009) |
| *Roommate ACA *HUM* | -0.055** | -0.022** |
| | (.024) | (.011) |
| *Female* | -0.502* | -0.321*** |
| | (.257) | (.105) |
| *Female*SOC* | 0.587 | 0.354** |
| | (.358) | (.145) |
| *Female*HUM* | 0.078 | 0.210 |
| | (.397) | (.172) |
| *Course of Study Dummies* | yes | Yes |
| *Observations* | 1228 | 1228 |
| *R-squared* | 0.49 | 0.38 |

Note: see Table 3

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