

Be as careful of the books you read as of the company you keep. Evidence on peer effects in educational choices*

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Abstract

In this paper we investigate whether peers' behavior has an important and significant effect on the choice of college major using a unique dataset from a highly selective Italian university. The available data and the peculiar structure of the degree allow us to identify the endogenous effect of peers on this decision, circumventing the two crucial identification problems of studies of social interactions: endogeneity and reflection. Peer-groups are defined using information on randomly assigned teaching classes, where the randomization is repeated for each course (i.e. 9 times in three semesters). This allows to construct peer-groups that vary at the level of the single student, thus solving the well-known reflection problem. Results show that, indeed, one is more likely to choose a major when many of his/her peers make the same choice. We estimate that, when it diverts students from majors in which they seem to have a relative ability advantage, this effect leads to lower average grades and graduation mark, a penalty that on the labour market could cost up to 580 euros (744 USD) a year.

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1 Introduction

Peer behavior and peer quality are commonly believed to be among the most important determinants of many individual outcomes (Katz and Case, 1991; Hoxby, 2000; Sacerdote, 2001; Duflo and Saez, 2002), particularly so for young people and their educational and early labour market decisions. The identification of these effects is however very problematic due to the presence of two well known issues: the endogenous sorting of individuals into groups of peers and the reflection problem (Manski, 1993).

The contribution of this paper to the literature is twofold. On the methodological side, we develop a new strategy for the identification of endogenous peer effects by exploiting a very detailed set of data about undergraduate students from Bocconi University and the peculiar structure of the degree programs offered by this institution. The second contribution is more substantial. In contrast to most studies in this literature¹, which have typically looked at either academic or labour market performance, we estimate the role of peer-effects on individuals' choices of college major (although our identification strategy can be fruitfully employed for other contexts as well). In most industrialized countries, skill mismatch is a major issue and, at least part of it, is thought to be due to a slow response of educational choices to changes in the composition of labour demand (Katz and Murphy, 1992). It is therefore important to understand how these choices are made and peer influence is likely to play a crucial role.

Our econometric methodology differs from most of the existing literature that tries to recover peer effects using either natural experiments (Sacerdote, 2001; Zimmerman, 2003) or quasi-experimental designs (Hoxby, 2000), or fixed effects (Hanushek et al. 2003). We take a different approach and exploit the possibility offered by our data to construct peer groups that vary at the level of the single individual.

At Bocconi University², students initially enroll in a common program and only at the end of the third semester (i.e. after 1 and 1/2 years) choose whether to specialize in business or economics. During these first 3 semesters all students take 9 compulsory courses and attend lectures in randomly assigned teaching classes. Since the number of available teachers varies for each course,

¹With the exception of Sacerdote (2001), where, however, no significant endogenous peer effect is found for the choice of major.

²This university offers only courses in business and economics (see section 2 for further details).

the assignment of students to classes is repeated for each course, as explained in Section 2.

This setting allows to define peer groups using information on teaching classes. In other words, we assume that student i interacts with the students who attend lectures in the same class and we weight peers by the number of classes taken together (up to 9). We, thus, obtain peer groups that vary at the individual level: student i 's peers certainly study with i but also with other students who are not necessarily members of i 's peer group. Consequently, the peer groups of i and i 's peers do not coincide, thus eliminating reflection.

Moreover, since the allocation in teaching classes is random (according to an ad hoc algorithm designed by the IT services of the university), there should be no endogeneity in peer group formation. Additionally, our data also contain a very rich set of observable proxies for those variables that are commonly believed to induce self-selection (i.e. ability, motivation, preferences etc.). In fact, the dataset includes detailed information on high school performance (school type and average grades in each of the two final years) and university admission procedures (i.e. standardized entry test and stated preferences over the various programmes offered by the university).

This particular repeated randomization process distinguishes our approach from most previous studies (Sacerdote, 2001; Zimmerman, 2003) where the randomized assignment - when there is one - is typically done only once and for all. In our set up, the allocation of students into classes is repeated for each course (i.e. 9 times over the first 3 semesters) given that the number of teachers is not evenly spread across courses (i.e. mathematics has more teachers than economics I) and the capacity of the available classrooms also varies considerably. This leads to peer groups that vary at the level of the single student and allows to solve the usual reflection problem.

Thus, the combination of the particularly rich dataset, the repeated randomization process and the peculiar construction of the peer groups allows us to solve the two key econometric problems of this literature: reflection and selection.

The spirit of our identification strategy is similar to Bayer et al. (2004), a study of criminal behavior that exploits the length of the individual's sentence to weight each peer's characteristic by the time spent together in the same correctional institution. Bayer et al. (2004) find that peer characteristics do influence recidivism in a number of outcomes such as burglary, felony drug use, etc.

With this approach we are able to identify the causal effect of peers' choice of major (economics

vs. business) on one's own decision. Results show that, indeed, one is more likely to choose a major when many of his/her peers make the same choice. We, then, look at whether students who specialize in a major following the choices of their peers and against their revealed relative ability (measured as the ratio of one's average grade in economics and business courses during the first three semesters) perform better (in terms of average grades in the last three semesters, graduation mark and time to graduation) than similar students who chose the major against the majority of their peers and according to their revealed ability. Our findings indicate that, indeed, there is a negative effect of following one's peers when revealed ability would suggest a different choice. We, then, try and assign a monetary value to this effect by looking at the wage cost of such a lower academic performance.

Every study of peer effects and social interactions has to deal with two crucial issues for the correct interpretation of the results: the definition of the mechanism through which an individual is affected by the behavior of her peers and the identification of meaningful peer groups.

As for the first issue, we can think of at least three mechanisms that are potentially important in our particular framework. First, peer pressure (Mas and Moretti, 2006), being it monitoring or imitation, might be substantial in leading a student towards a particular major choice. Second, there might simply be a utility gain in studying with friends. Third, peers may also facilitate the acquisition of information (or constitute a reference group in the formation of expectations) about various aspects of life at the university (where to find the right material to study, which are the best or the easiest courses, the best teachers, etc.) and about the job opportunities associated with a particular major.

Unfortunately, our research design does not allow to test which of these mechanisms generates the effects detected by our estimates. However, it seems plausible to rule out the possibility that these effects are generated by peers providing easier access to information. If this was the case, in fact, better informed individuals should on average make better choices and this is at odds with our findings in terms of time to graduation, average grades and graduation mark³.

Besides the identification of a specific mechanism that generates peer effects, it is also crucial

³Another potentially important issue is compensating wage differentials. A student might be willing to give away part of her wage to derive utility from sticking with her friends. In our particular context, however, this does not sound like a fully convincing argument because students typically have very limited information about the wage distributions associated with the two majors (economics and business) at the time of making their choice. Furthermore, the two ex-post distributions look very similar.

to focus on meaningful peer groups. It would be hard to justify that the behavior of a random pedestrian in San Francisco should influence the decision not to stop at a zebra crossing in Milan. In our particular framework, some students might be in the same class but their interactions might still be limited. We address this problem by weighting peers in each group by the number of courses attended together so that in the peer group of a generic individual i , students who have attended all common courses in the same teaching classes as i will be given a higher weight than students who have taken only a few courses together. It is likely that students who sit several classes together will get to know each other and often interact socially as well as for studying and revising the subject⁴.

The paper is organized as follows: Section 2 describes the institutional structure of Bocconi University, the available data and the details of the allocations into the teaching classes; Section 3 presents our approach for the construction of the peer groups; Section 4 discusses the identification strategy and the results of the analysis of the choice of major. Section 5 discusses the effects of the decision modes on average GPA, graduation mark and time to graduation. Finally, Section 6 concludes.

2 Data and institutional details

The analysis in this paper is based on administrative data from Bocconi University, an Italian private institution of higher education with core specialization in business and economics. The data provide detailed information on the university curricula of all students enrolled at Bocconi since 1989.

Until the academic year 1999/2000, the most popular degree offered by Bocconi was called CLEA/CLEP. Students in this degree would first take a series of 9 common exams during the first three semesters and would, then, choose whether they wanted to specialize in business (CLEA) or economics (CLEP) (See Figure 1). The 9 common compulsory courses are listed in Table 1 and can be classified in subject areas, according to the department responsible for organizing and teaching: business, economics, quantitative subjects and law.

[FIGURE 1 and TABLE 1]

⁴The authors here could themselves provide a number of telling anecdotes.

In the academic year 1999/2000 Bocconi introduced a major reform of its structure (the so-called "Bocconi 2000" plan), abandoning this initial common track and forcing students to choose between economics and business since the beginning of their studies. Moreover, the information on the randomly allocated teaching classes has unfortunately been lost for the earlier cohorts of students and is reliable only starting with the academic year 1998/1999. This forces us to use only one cohort of students, i.e. students enrolled in the old CLEA/CLEP program in the academic year 1998/1999.

At that time, Bocconi offered 4 other degree programs: one in "Economic and Social Sciences" (DES), one in "Economics of Financial Market Institutions" (CLEFIN), one in "Management of the Public Administration and International Institutions" (CLAPI) and one in "Law and Business Administration" (CLELI)⁵. These degree programs differ both in their curricula and in the number of students admitted in each academic year⁶. In September 1998, a total of 2,580 students were admitted and 2,055 of them eventually enrolled at Bocconi⁷.

When sitting for the admission test, each prospective student had to rank the 5 programs according to her preferences. Then, the Admission Committee ranked candidates on the basis of their test results and high school academic performance. Starting from the top of the ranking, students were assigned to their preferred programs depending on availability. Specifically, a student was assigned to her first choice if there were still places available in that program, otherwise, if all places in the first choice had already been taken by students higher up in the ranking, the candidate was assigned to her second choice and so on if the second choice was also full. It is important to notice that in this mechanism a student's stated preferences across the 5 programs do not influence the probability of being admitted and thus excludes any strategic behavior.

Admitted candidates who decided not to register freed places for students further down in the ranking. However, only a few students (48 out of the 753 rejected candidates) who had been initially rejected took up a place freed by others, possibly because at the time of making these decisions most people had already obtained admission to another university and started to make arrangements for

⁵Created in 1970, CLEA (Degree in Business Administration) and CLEP (Degree in Economics) are the oldest degrees offered at Bocconi University. Four years later, they were joined by DES, a more quantitative and academic version of the CLEP. All the other degrees (CLEFIN, CLAPI and CLELI) were introduced in 1990 with the "Bocconi 2000" development plan.

⁶Enrolment ceilings and admission tests were introduced in 1984.

⁷We are excluding students transferring from other universities and students from abroad who were given a few reserved places.

the registration and the accommodation⁸.

Eventually, the admission procedure in September 1998 led to 1,385 students (against a ceiling of 1600) enrolled in the common CLEA/CLEP track, followed by CLELI (239 against a ceiling of 350), CLEFIN (208 against a ceiling of 230) CLAPI and DES (respectively with 132 and 91 against ceilings of 200 each). Once enrolled, there were a few possibilities to switch across programs. CLEA/CLEP students were not allowed to switch to any of the others degrees, while students coming from CLELI, CLEFIN, CLAPI and DES could move to CLEA/CLEP after the first academic year.

[TABLE 2]

Students admitted into the 5 programs differ both in their previous high school records and in their performance in the admission test (Table 2). On average, CLEA/CLEP students have the lowest high school final grade, but perform better than CLELI students in the admission test and eventually reach higher positions in the final entry ranking (which is constructed as a weighted average of admission test score, high school final grade and average grades in the last 3 years at high school).

Overall, however, these differences are minor and preferences more than ability per se seem to be the predominant factor in determining the self-selection of students into the degree programs. In fact, the percentage of students admitted to the degree of their first choice was close to 90%.

In this paper we will focus exclusively on students enrolled in the CLEA/CLEP common track. For our purposes the selection of students into different programs is a minor issue which we leave for a future version of the paper. Excluding a few missing values on our variables of interest and those students who did not complete the courses of the first 3 semesters, our working sample consists of the 1,122 observations described in Table 3. All of these students have complete information about their courses in the initial three semesters. About a 100 of them have not graduated, either because they dropped out, changed university or are still enrolled and trying to graduate.

[TABLE 3]

⁸Note also that candidates in the lower tail of the distribution of the admission test were not offered any of these residual places.

After the first 3 semesters of common courses, each student originally enrolled in CLEA/CLEP had to choose whether to specialize in business (CLEA) or in economics (CLEP). Table 4 reports some descriptive statistics on the ability and performance of these two groups of students.

[TABLE 4]

Considering all the common exams in the first three semesters, the 146 students choosing CLEP score on average almost 2 grade-points above CLEA students. This difference is even higher when the exams are disaggregated by field. As expected, CLEP students perform relatively better in economics, while the difference is considerably smaller for the average grade in business exams, suggesting - as we will see more formally later on - that students choose their field of specialization according to their relative abilities or interest. Furthermore, the difference in the average grade of the exams of the quantitative area is also very large, reflecting the nature of the CLEP program that was considerably more quantitative than CLEA.

2.1 Teaching classes

Depending on the number of available lecturers, a certain number of teaching classes were created for each of the 9 common courses. Moreover, the capacity of the available classrooms at Bocconi varies considerably and the number of students in each teaching class had to be determined accordingly.

Students were allocated to teaching classes randomly for each course. The decision to adopt a random allocation algorithm was dictated by the need to avoid congestion in the classrooms that could be generated by students wanting to attend lectures with their mates or with the best teachers.

Towards the end of each term, students had to enroll in the courses of the following term either at the administration desk or through some electronic machines located in the university buildings⁹. Students were free to choose whether they wanted to postpone some of the courses (e.g. take a course of the second semester in the third and so on) provided they satisfied the pre-requisites for each exam (e.g. statistics could only be taken after having passed math)¹⁰. Moreover, students

⁹Enrolment in the courses of the first term of the first year was automatic.

¹⁰There are normally up to 7 exam sessions per year for each of the 9 common courses during the academic year.

who failed to pass an exam during the academic year in which they had attended the corresponding course, were required to re-register and were also assigned to a teaching class (together with other students). For these reasons, the total number of students enrolled in each course (the sum over all the classes) may vary slightly across courses.

At the time of enrolment, a random algorithm would assign the student to a teaching class and communicate the class number. The algorithm was designed to fill all classrooms at the same rate in order to obtain a final distribution with an adequate number of students in each classroom. By no means could the students interfere with the algorithm. For example, there was no guarantee that two students enrolling in the same course one right after the other would be placed in the same teaching class (and, in fact, despite the many that attempted to do so, this instance was extremely rare).

In principle, students were required to attend lectures in their assigned teaching classes but enforcement varied a lot over time, becoming stricter and stricter in more recent years. Actually, the evolution of enforcement practices is closely related with the availability of the information of teaching classes: as the enforcement of the allocations was made more and more stringent, teaching classes were also recorded on various official documents and thus maintained in the administration's archives.

The mere fact that teaching classes have been carefully recorded for the 1998/1999 cohort¹¹ is an indication that the system was effectively enforced. Students were forced to attend their classes by various methods. First, lecturers were supposed to circulate attendance sheets at the beginning of the class for students to sign their presence. Obviously, with a large number of students in each class (the average class size was 202 students), this method could be easily circumvented by those who wanted to attend a different class by, for example, having some friends signing for them. Mid-terms were also important in encouraging students to attend their assigned classes. In fact, while the final exams were identical for all students regardless of their classes, mid-terms were organized directly by the lecturers. Therefore, if a student wanted to take the mid-term (which were not compulsory but highly recommended and very popular among the students) she'd better attend her assigned class as the exam was prepared and marked by the same lecturer.

¹¹There are less than 2% of missing values.

[TABLE 5]

Table 5 describes the average characteristics of the teaching classes for each course. The number of classes ranges from 4 (private and public law) to 10 (mathematics, management and accounting) and the average number of enrolled students varies accordingly. The other variables in Table 5 are derived from students' questionnaires. At the end of each course¹², in fact, students were distributed a standardized anonymous questionnaire designed to collect their opinions about numerous aspects of the teaching (quality of the lectures, logistics, etc.).

The number of completed questionnaires is a one-off measure of attendance, as it should correspond to the number of students present in class on the day the questionnaire was distributed. Attendance is also self-reported by the students in the questionnaire, where they have to indicate the fraction of lectures they attended for that course. These figures indicate that attendance was typically very high, with students being present at over 80% of the lectures for economics, management and quantitative courses. Only law subjects have slightly lower attendance levels, around 75-80%.

The number of completed questionnaires, compared with the number of enrolled students, is also an indicator of possible congestion due to students not going to their assigned classes. Table A.1 in the appendix reports statistics for each teaching class and shows that in some cases (math, class 10; accounting, class 4 and economics I, class 3) there are more questionnaires than enrolled students. This means that on the day of the questionnaire there were more students in the class than those assigned by the administration. This typically happens for the most difficult courses, where students tended to cluster in the classes of the best lecturers.

The questionnaire also includes a specific question on congestion that reads as follows: "*For your learning, the number of students attending your class has been: insufficient (1), too low (2), ideal (3), too high (4), excessive (5)*". Tables 5 and A.1 report the average score of this question across courses and for each single class, respectively. This information is very important for our identification strategy, as we describe in the following section.

¹²Normally, during one of the lectures in the last week of the term.

3 Peer group definition

Our definition of peer groups is based on students attending courses in the same teaching classes. More precisely, individual i 's peer group (G_i) includes all individuals j who were assigned to the same teaching class as individual i for at least one of the 9 common courses. Furthermore, each of the $j \in G_i$ is given an importance weight, $\omega_{ij} \in (0, 1]$, according to number of the common exams taken together with i . When computing the absolute size of peer groups the weights are simply constructed as the fraction of common exams taken together, i.e. $\omega_{ij} = 1$ if j attends all 9 courses in the same teaching class as i , $\omega_{ij} = 1/9$ if j attend only 1 course with i . In all other calculations (including the estimation exercises in the following section), the weights are normalized to sum to one within each peer group.

The underlying assumption of this definition of the peer groups is that students make friends with other students during lectures. They, then, go out, study and prepare exams together and will eventually influence each others' choices. However, there are a couple of reasons why many of the students in i 's peer group may not have much of a relationship with i . First, some of these students may only take a very limited number of courses with i . The weighting scheme described above that assigns a higher weight to students who attend more classes together, should take account of this¹³.

Second, as mentioned in the previous section, for some courses the allocation into teaching classes was not effectively maintained by the students, especially for the most difficult courses where attending lessons with a good lecturer may be extremely helpful for the final exam. We take account of this second problem by repeating our estimation exercises by also weighting courses in the definition of the peer-groups.

Courses in which the system of randomly allocated teaching classes was not effectively maintained should show a large variation across classes in the measures of congestion, i.e. there should be some classes with very many students and others with very few students. We, then, construct course weights, ξ_c , by assigning weight 1 to the course with the lowest maximum level of reported congestion across classes (i.e. 2.51 for Management II) and the weights of the other courses are scaled down accordingly. More specifically, ξ_c is the ratio between the lowest maximum level of congestion and the maximum level of congestion across the classes of each course. These weights

¹³The weights adopted in this version of the paper are linear in the number of courses attended together. We have experimented with many other specifications and results are robust.

are reported in the last column of Table 5.

The version of the individual weights that incorporates the ξ_c 's is constructed as follows:

$$\omega'_{ij} = \frac{1}{9} \sum_{c=1}^9 \xi_c \mathbf{I}_{ij}^c$$

where \mathbf{I}_{ij}^c is an indicator function equal to 1 if i and j were assigned to the same teaching class in course c . As for ω_{ij} , also these weights are used in this raw format to compute the absolute size of the peer groups and they are normalized to sum to one within each peer group for all other calculations.

Other definitions of the course weights have been experimented, in particular one that assigned weight 1 to the course with the lowest coefficient of variation of the congestion measure (i.e. 0.04 for Private Law) and scaled down the other courses accordingly. Results are robust to different specifications of the ξ_c 's.¹⁴

[TABLE 6]

Table 6 reports some descriptive statistics of the peer-groups according to our definition. The unweighted group size, i.e. the average number of individuals who attended at least one class together, corresponds broadly to 80% of the overall size of the cohort. However, when weighting each of the peers in a student's peer group according to the number of classes taken together (column [1]), the average peer group's size decreases by almost 80%. Augmenting the individual weights with course weights based on congestion (as explained earlier on) leads to a further reduction of about 8% (column [2]). As expected, the use of congestion weights, which give less weight to more congested courses, also significantly reduces the average number of classes taken together.

¹⁴In an earlier version of the paper we also defined peer group based on sitting an exam in the same session. This definition is obviously affected by self-selection since similarly able students would sit an exam in the same session. In fact, in this earlier version of the paper any evidence of peers' effect disappeared once we controlled for a number of ability measures (i.e. entry tests, high-school grades, etc.). We find this to be crucial evidence in a twofold sense: (1) the definition of the peer group is fundamental in identifying social interactions and (2) the fact that our results are robust to controlling for ability corroborates our entire analysis.

4 Peer effects in major choices

The identification of endogenous social effects has been the topic of several papers (Manski, 1993 and Moffit, 2001 to cite just a few) and it rests on two distinct dimensions: endogeneity and reflection. First, in most cases individuals self-select themselves into a group of peers generating a standard problem of endogeneity if the variables that drive this process of selection are not fully observable. A second and more subtle issue arises because in a peer group everyone's behavior affects the others and, as in a mirror reflection, we cannot know if one's action is the cause or the effect of peers' influence.

Let us start with a discussion of how we address reflection. This problem has been commonly described by using a simple linear model of the following type:

$$y_i = \alpha + \beta E(y|G_i) + \gamma E(\mathbf{x}|G_i) + \boldsymbol{\theta}\mathbf{z}_g + \boldsymbol{\delta}\mathbf{x}_i + u_i \quad (1)$$

In our framework, y_i is the chosen major (i.e. economics or business), \mathbf{x}_i is a set of individual traits, $E(\mathbf{x}|G_i)$ contains the averages of the \mathbf{x} 's in the peer group of individual i , denoted by G_i and \mathbf{z}_g are characteristics of the peer group. Following the literature, β measures the endogenous effect, γ the exogenous effects and $\boldsymbol{\theta}$ the correlated effects.

In the standard framework, peer-groups are fixed across individuals, i.e. if A and B are both in the peer group of C, it must also be that A and B are in the same group. Put in the wording of equation (1), if i and j are in the same peer-group, then the two groups coincide, i.e. $G_i = G_j$. In this situation, endogenous effects cannot be distinguished from contextual or correlated effects (Manski, 1993). In fact, it is easy to show, by simply averaging equation (1) over group G_i , that $E(y|G_i)$ is a linear combination of the other regressors:

$$E(y|G_i) = \left(\frac{\alpha}{1 - \beta} \right) + \left(\frac{\gamma + \boldsymbol{\delta}}{1 - \beta} \right) E(\mathbf{x}|G_i) + \left(\frac{\boldsymbol{\theta}}{1 - \beta} \right) \mathbf{z}_g \quad (2)$$

In our framework peer groups are individual specific. Consider the simple case of only three students. Students A and B study together (e.g. they attend 5 courses in the same classes), however, B also studies with C (e.g. they attend some of the remaining 4 courses in the same class, different from A's class). A's peer group, thus, includes only B while B's peer group includes both A and C.

This identification can also be seen as a case of triangularisation, i.e. in the standard simultaneous equation model at least one exogenous variable is excluded from each equation. Here, A is excluded from the peer group of C, who is excluded from the peer group of A.

With 9 courses, each divided into 4 to 10 teaching classes, our data exhibit enough variation to generate peer-groups that vary at the level of the single individual, e.g. every student has a different peer-group. The weighting scheme described in the above section adds even more variation to the individual peer groups.

To formally see the advantage of our framework in solving the reflection problem, rewrite equation (2) allowing peer-groups to vary at the level of the single individual:

$$E(y_i|G_i) = \alpha + \beta E[E(y|G_j)|G_i] + \gamma E[E(\mathbf{x}|G_j)|G_i] + \boldsymbol{\theta}\mathbf{z}_g + \boldsymbol{\delta}E(\mathbf{x}_i|G_i) \quad (3)$$

where j is a generic member of i 's peer group. The key to understanding this equation is the fact that j 's peer group G_j does not necessarily coincide with G_i .

We further simplify the specification of equation (1) by assuming that $\boldsymbol{\gamma} = \boldsymbol{\theta} = \mathbf{0}$. This assumption is both necessary and innocuous. Our peer groups are randomly determined and therefore there are no purely correlated effects ($\boldsymbol{\theta} = \mathbf{0}$), i.e. there are no variables that pertain exclusively to the characteristics of the groups such as the \mathbf{z}_g 's. Moreover, again because of the random allocation process, $E[E(\mathbf{x}|G_j)|G_i] = E(\mathbf{x}|G_i)$, which is a linear combination of the \mathbf{x}_i 's, hence in equation (1) it is sufficient to control for \mathbf{x}_i ¹⁵.

The second identification issue is endogeneity. In our framework, peers are defined by the process of repeated random allocation into teaching classes, which is exogenous by definition. Moreover, our data include several observable proxies for variables that are generally unobservable to the econometrician (i.e. standardized ability test, high-school grades, type of high-school, motivation, etc.) and we make use of all of them to purge our results from potential residual endogeneity.

It should, however, be mentioned that, although we are able to create well defined peer groups, these may not capture all and only the truly important peers, i.e. those with whom a subject interacts regularly. Weighting peers by the number of courses attended together partly addresses

¹⁵Actually, $E(\mathbf{x}|G_i)$ is not exactly a linear combination of the \mathbf{x}_i 's because of the weighting scheme, which is different for each student i . However, this is not sufficient to guarantee enough variation for identifying $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ separately.

this issue, however, it is perhaps safer to interpret our results as lower bounds of the true peer-effects.

[TABLE 7]

To document the absence of self-selection into peer-groups in our setup, Table 7 reports the correlation coefficients between individual and group averages of some selected measures of ability for various definitions of peers. In column [1] peer groups are constructed considering all 9 common exams equally, i.e. without weighting courses by their level of congestion. In column [2], peers are weighted not only by the number of courses taken together but also by the congestion level of each course, as described in section (3). In column [3] we exclude from the construction of the peer groups the three most congested courses according to the course weights reported in Table 5, i.e. economics II, mathematics and statistics. Finally, in column [4] we also exclude the fourth most congested course, i.e. management II.

The numbers in Table 7 show that peers are not clustered by most of the ability measures considered. A small and mildly significant correlation exists for the average grade in the common business courses (which is, however, negative) and for the number of exams taken on the first available session. As discussed by Altonji et al. (2005), if selection on observables and unobservables follow the same pattern, these results indicate that peers are selected randomly along both dimensions. This result is obviously not very surprising given that our peer-groups are based on randomly assigned teaching classes.

4.1 Results

As already mentioned Bocconi University is a highly specialized institution offering only degrees in economics, management and, only in very recent years, law. In particular, the CLEA/CLEP program offered only two majors: economics and business. While the first three semesters were common to all the students, the remaining five were clearly differentiated between the two majors¹⁶.

The choice of college major is one of the most important decisions undergraduates make and it clearly affects their future careers and earnings. Sacerdote (2001) did not find significant influence

¹⁶Although some elective courses could be picked from any of the two majors, nevertheless such practice was quite uncommon and the number of such options very limited.

of peers in such a decision while a significant effect was there found for GPA and the decision to join a fraternity. However, in his framework peer groups were defined on the basis of random assignment to rooms in campus dorms. While this method has the clear advantage of potentially eliminating the bias from endogenous sorting, it is not obvious that roommates are the right group of peers to look at for our specific problem. In our data, peer groups should include students who attend courses and plausibly prepare exams together.

To estimate the effect of peers on one's decision to specialize in economics versus business, we run a probit regression similar to equation (1) with the exception that we assume $\boldsymbol{\gamma} = \boldsymbol{\theta} = \mathbf{0}$:

$$y_i = \alpha + \beta E(y|G_i) + \boldsymbol{\delta}\mathbf{x}_i + u_i \quad (4)$$

where $y_i = 1$ if a student chooses economics and 0 otherwise. $E(y|G_i)$ is the % of peers choosing economics (weighted by the number of exams taken together and normalized to sum to 1) and \mathbf{x}_i is a set of controls for individual characteristics that includes a gender dummy, household income (as recorded at the first registration), a dummy for students who reside outside the city of Milan (the site of Bocconi), a set of dummies for the region of origin, a series of controls for academic performance and ability (high-school grades and type, average grades in the common exams average grade in the quantitative common exams, the ratio between the average grade in the common economics and business exams and the number of common exams taken on the first available session).

[TABLE 8]

Table 8 reports the results of the estimation of equation (4) in the form of marginal effects for the average student in the sample for various definitions of peer-groups. In the first column, peer groups are constructed considering all 9 common exams equally, i.e. without weighting courses by their level of congestion. These estimates indicate the presence of peer effects in major choice. In particular, a one percentage point increase in the (weighted) fraction of peers opting for economics raises the probability of making the same choice by over one half of a percentage point (that is 5 percent over the average value).

This result is extremely robust across the other 3 columns of Table 8, that repeat the same estimation using different definitions of the peer groups. In column two, peers are weighted not

only by the number of courses taken together but also by the congestion level of each course, as described in section (3). In column three we exclude from the construction of the peer groups the three most congested courses according to the course weights reported in Table 5, i.e. economics II, mathematics and statistics. Finally, in column four we also exclude the fourth most congested course, i.e. management II.

A few other results from Table 8 are worth mentioning. Revealed ability heavily influences the choice of major: in fact, students tend to specialize in the subject in which they have performed better during the initial common semesters. This is shown by the positive coefficient estimated on the ratio between the average grade obtained in the common courses of the economics (economics I and II) and the business (management I and II and accounting) area. Also, the positive and significant coefficient estimated on the average grade in all the 9 common courses indicates that the best students typically choose economics.

Finally, it is probably worth noticing that these results are obtained conditioning on a number of controls rarely available to the econometricians, such as entry tests, high school grades, number of exams taken on first available sessions, etc.

5 Are books better than company?

In this section we analyze the relationship between students' academic performance in the second half of their degree (i.e. the non-common semesters) and how they chose their major, i.e. based more on their own revealed ability or on their peers' behavior.

To this purpose, we construct two indicators. The first one, f_i , measures the relative fraction of peers who made one's same choice of major. Suppose individual i chose to specialize in economics, then f_i is computed as the ratio between the (weighted) fraction of i 's peers who also chose economics and the fraction of all students in the sample who chose economics. If $f_i > 1$ it means that in i 's peer group there is a higher than average incidence of students in economics. Similarly for students who chose business. More formally, f_i is defined as follows:

$$f_i = \begin{cases} \frac{\sum_{j \in G_i} \omega_j ECON_j}{N^{-1} \sum ECON_j} & \text{if } ECON_i = 1 \\ \frac{\sum_{j \in G_i} \omega_j BUSINESS_j}{N^{-1} \sum BUSINESS_j} & \text{if } BUSINESS_i = 1 \end{cases} \quad (5)$$

where $ECON_i$ is a dummy variable equal to 1 if student i chooses economics and zero otherwise (similarly for $BUSINESS_i$).

The second indicator, g_i , is a measure of relative ability. Our data include very detailed information on each exam, including the grade. We consider the nine common exams taken during the first three semesters and group them into areas - economics, business, quantitative and other - as described in Section 2. Suppose individual i chooses to specialize in economics, then g_i is computed as the ratio between i 's average grade in the exams of the economics area over i 's average grade in the exams of the business area. Similarly for students who chose business. Formally, g_i is defined as follows:

$$g_i = \begin{cases} \frac{GPA_i^{ECON}}{GPA_i^{BUSINESS}} & \text{if } ECON_i = 1 \\ \frac{GPA_i^{BUSINESS}}{GPA_i^{ECON}} & \text{if } BUSINESS_i = 1 \end{cases} \quad (6)$$

where GPA_i^{ECON} is i 's average grade in economics' exams and $GPA_i^{BUSINESS}$ is i 's average grade in business' exams. If $g_i > 1$ it means that during the first three semesters student i has performed better in the exams of the major she eventually chose as a specialization. Note that in constructing this indicator we only consider the common exams of the first three semesters, namely economics I and II for economics and management I and II and accounting for business.

We, then, use these indicators to define four groups of students. The first group, which we label *ability driven*, includes those students who chose the major subject in which they performed better during the first three semesters against the (relative) majority of their peers, i.e. $f_i < 1$ and $g_i > 1$. The second group - the *peer driven* - are students who chose as the (relative) majority of their peers and against their revealed ability, i.e. $f_i > 1$ and $g_i < 1$. The third group - the *coherent* - includes those students who made a choice of major that is coherent with their performance as well as with their peers' behavior, i.e. $f_i > 1$ and $g_i > 1$. Finally, some students - the *incoherent* - chose against both their academic record and their peers, i.e. $f_i < 1$ and $g_i < 1$. Table 9 summarizes these definitions.

[TABLE 9]

As the table shows, students are rather evenly spread across the four groups. The largest group is the *coherent*, i.e. students who choose both according to their ability and their peers. Slightly

less (about 30%) choose against the relative majority of their peers and following the signal of their revealed performance. A smaller, but yet sizeable, number of students (about 18%) follow their peers in contrast with the indication of their academic performance. Finally and perhaps surprisingly, there still is a large residual category of students (about 18%) who seem to make a decision against both peers and revealed ability.

We use these groups to estimate the effect of these four decision modes on three academic outcomes: average grade in the last two and a half years of the degree (i.e. after the major choice is made), graduation mark and time to graduation. A general specification of the equations that we estimate in this section is the following:

$$y_i = c + \pi_1[\text{peer driven}]_i + \pi_2[\text{coherent}]_i + \pi_3[\text{incoherent}]_i + \boldsymbol{\vartheta}\mathbf{x}_i + u_i. \quad (7)$$

where y is the outcome considered and the other variables are dummies that identify the groups (with the *ability driven* kept as a reference group). The set of controls - \mathbf{x}_i - includes a gender dummy, household income (as recorded at first enrolment), a dummy for students who reside outside the city of Milan, a set of dummies for the region of origin, a series of controls for academic performance and ability (high-school grades and type, average grades in the common exams, a dummy for the specialization and the number of common exams taken on the first available session).

[TABLE 10]

The results of this exercise are presented in Table 10. Column two and four extend the specification for average grades in the non-common courses and graduation mark with time to graduation. In column five, when we look at time to graduation, we replace the average grade in the common courses with the average grade in all courses. Notice that the maintained assumption is that, conditional on the observables, the four categories are independent from the outcome variable¹⁷.

Although the effect is small in magnitude, there is clear evidence that *peer driven* students on average perform worse than the *ability driven* in terms of average grades and final grade, while there seems to be no detectable difference in time to graduation. We estimate a significant negative

¹⁷A basic version of a Conditional Independence Assumption (CIA), where selection is on observables and we can control for all those variables affecting both the decision mode and the outcomes considered.

effect of -0.16 to -0.2 of a grade point on the average grade in non-common exams (exam grades are given on a scale from 0 to 30 with pass equal to 18) and of -0.6 to -0.7 on the final grade (given on a scale 0 to 110 with pass equal to 66). These results are robust to a series of robustness checks.

5.1 Labor market effects

In this section we try and assign a ‘price’ to the decision of following one’s peers in contrast with one’s revealed ability (i.e. being a *peer driven* student as opposed to an *ability driven*) in terms of entry wages. The ideal strategy to do this would be one in which entry wages for the same students used for the estimation of equation (7) are regressed on the dummies for the decision modes, controlling for a set of individual characteristics. Unfortunately, information on wages is only available in a dataset constructed by Bocconi university by interviewing almost all its graduates¹⁸ one and a half years after leaving university and these surveys currently cover only graduates between 2000 and 2003. Only for about 1/3 of the observations used in the previous sections of this paper it is possible to recover information on labour market outcomes from these surveys and this is obviously a very selected group of early graduates.

For these reasons, we take a different approach and merge academic records with all available surveys of graduates to compute the penalty associated with a lower graduation mark for the whole sample of Bocconi students who graduated between 2000 and 2003. The data on labour market outcomes include information on wages in the first job, the type of occupation and contract and a number of questions on satisfaction with the university.

In Table 11 we report the results of these estimates. In these regressions we are mostly interested in the coefficients on graduation mark but we also control for time to graduation and the entire set of ability measures and individual traits that have been used throughout the paper. Moreover, since wages are recorded in intervals the results in Table 11 are produced with interval regressions¹⁹.

Results show a sharp discontinuity at the top of the distribution of graduation marks. In fact, when this variable is introduced linearly (column [1]) the estimated effect is relatively small: a one

¹⁸Several male students were on compulsory military service and others (both male and female) could not be reached.

¹⁹The same results have been produced with alternative econometric specifications (i.e. linear OLS on the mid-points of the intervals, quantile regression, ordered probit) and the magnitude and significance of the estimated effects are extremely robust.

point increase in the final grade raises monthly wages by a mere 6 euros (8 USD) per month - i.e. about 78 euros (100 USD) per year. However, this effect is much bigger for students obtaining full marks (i.e. 110 with or without honours), who earn almost 67 euros (86 USD) per month (871 euros-1,117 USD- per year) more than students who just fail to get full marks²⁰.

According to the results of Table 10, *peer driven* students obtain their degrees with approximately 2/3 of a graduation mark less than the *ability driven*. This means that choosing a major following one's peers and in contrast with one's revealed ability could lead to lower annual wages by about 52 euros (67 USD). This is admittedly a small number that could, however, go up to a sizeable 580 euros (744 USD) per year in case the student just fails to obtain full marks. Furthermore, if we were to consider a constant life-time loss of those amounts we would get on average a net present value loss of 1,092 euros (1,400 USD)²¹, unfortunately we cannot test whether the penalty of a *peer driven* decision is constant over time since at the time of writing no other information on later wages is available.

6 Conclusions

In this paper we investigate whether peers' behavior has an important and significant effect on the choice of college major using a unique dataset from a highly selective Italian university. The available data and the peculiar structure of the degree allow us to identify the endogenous effect of peers on this decision, circumventing the two crucial identification problems of studies of social interactions: endogeneity and reflection.

As described in Section 2, students at Bocconi university initially enroll in a common program and decide whether they want to specialize in economics or business by the start of the fourth semester. In the initial three semesters they take nine common exams that are compulsory. During this initial period, students form ties and connections with their peers during lectures, classes and while preparing for the same exams. It is obviously not uncommon to get together for studying and revising a subject with a classmate, or discussing course material, possible choice of major and so

²⁰These results are broadly consistent with similar estimates produced on a different data source, i.e. the Bank of Italy Survey of Household Incomes and Wealth.

²¹The net present value (NPV) has been computed by assuming a constant interest rate of 5 percent and a life-time of 40 years. For those students at the margin of getting full marks the NPV loss would be a quite large 12,180 euros (15,620 USD).

on.

Our definition of peers is based on randomly assigned teaching classes to which students were assigned for the common courses of the first three semesters. The allocation of students into teaching groups was designed to facilitate lecturing by having classes of relatively small size. Moreover, this allocation was purely random given that (1) the number of available teachers for each course varied considerably and (2) venues capacity was not homogeneous across classrooms. Therefore, students were repeatedly reassigned to potentially different classmates for each of the nine common courses and this repeated random assignment generates peer groups that vary at the level of the single individual. Furthermore, from our data it is possible to know how many times two students were assigned to the same class and we can, then, weight peers accordingly, with the presumption that social interactions are stronger if repeated over time. We, thus, obtain peer groups where not every peer of individual A is in the peer group of B even if A and B are in the same group. Such a peculiar structure resolves reflection, while the mere random nature of class assignment eliminates any endogenous selection into peer groups.

There are, then, a whole class of social interactions that can arise in such a context: (1) peer pressure, being it imitation or monitoring; (2) utility from attending classes with the same group of mates; (3) peers providing a reference point both in terms of information or to form expectations for future outcomes. Unfortunately, we are not able to distinguish among these three types of social interactions, however, given the results in the last part of our analysis (Section 5.1), it seems reasonable to rule out the possibility that peers provide a good source of information on future career prospects.

In the first part of the analysis (Section 4) we focus on the identification of a clean endogenous effect. Results indicate the presence of a positive and significant effect of peers' choice of major on the probability of choosing that particular major, namely a one percentage point increase in the (weighted) fraction of peers choosing economics raises the likelihood of a student to choose economics by over one half of a percentage point (that is 5 percent over the average value). It is also interesting to notice that if we were to define peer groups on the basis of exams sat together (thus inducing endogenous sorting) we would estimate a stronger effect, which, however, cancels out once we control for our ability measures²².

²²As explained earlier on, in each academic year there are up to 7 exam sessions for each course and students can

In the second part (Section 5) of the paper we try to ‘price’ the effect of making a choice based more on peers’ behavior than on one’s revealed ability. Our results show that students who choose the same major as the relative majority of their peers and against their revealed ability (measured as relative performance in the courses of the economics and business areas during the initial three semesters) obtain significantly lower grades in subsequent exams and graduate with a slightly lower final mark.

Finally, we try to assign a wage value to the different decision modes that lead students to specialize in economics or business. As explained in Section 5.1, given the limitations of the available data, for this analysis we employ three cohorts of Bocconi graduates, between the years 2000 and 2003. We find that choosing a major following one’s peers and in contrast with one’s revealed ability could lead to lower annual wages by about 52 euros (67 USD). This could be considered a small amount, however, it could go up to a sizeable 580 euros (744 USD) per year in case the student just fails to obtain full marks. Furthermore, assuming this loss is constant over time, the net present value of this amount could be as high as 1,092 euros (1,400 USD), unfortunately we cannot test whether the penalty of a *peer driven* decision is constant over time since at the time of writing no other information on later wages is available.

References

- [1] Altonji, J.G., Elder, T.E., Taber, C.R., (2005), "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools", *Journal of Political Economy*, 113 (1): 151-183.
- [2] Case, A. and Katz, L., (1991), “The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youths”, NBER Working Paper: 3705.
- [3] Duflo, E. and Saez, E. (2002), “The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment,” unpublished working paper, MIT and University of California, Berkeley.

freely choose when to sit an exam. Plausibly, the best students tend to sit their exams at the first available date.

- [4] Hanushek, E., Kain, J., Markman, J. and Rivkin, S., (2003), "Does Peer Ability Affect Student Achievement?", *Journal of Applied Econometrics* 18(5): 527-544.
- [5] Hoxby, C., (2000), "Peer Effects in the Classroom: Learning from Gender and Race Variation", NBER Working Paper: 7867.
- [6] Katz, F. L. and K. M. Murphy (1992). "Changes in Relative Wages, 1963-1987: Supply and Demand Factors". *The Quarterly Journal of Economics* 107(1): 35-78.
- [7] Manski, C., (1993), "Identification of Endogenous Social Effects: The Reflection Problem", *Review of Economic Studies*, 60: 531-542.
- [8] Mas, A. and Moretti, E., (2006), "Peers at Work", mimeo, UC Berkeley.
- [9] Moffitt, R., (2001), "Policy Interventions, Low-Level Equilibria, and Social Interactions", in *Social Dynamics*, S. Durlauf and H. P. Young eds., Cambridge: MIT Press.
- [10] Sacerdote, B. (2001), "Peer Effects with Random Assignment: Results for Dartmouth Roommates," *Quarterly Journal of Economics*, 116: 681-704.
- [11] Zimmerman, D., (2003), "Peer Effects in Higher Education: Evidence from a Natural Experiment, Williams Project on the Economics of Higher Education", *Review of Economics and Statistics*, 85(1): 9-23.

FIGURE 1: Degree structure (academic years 1989-1990 to 1991-1992)

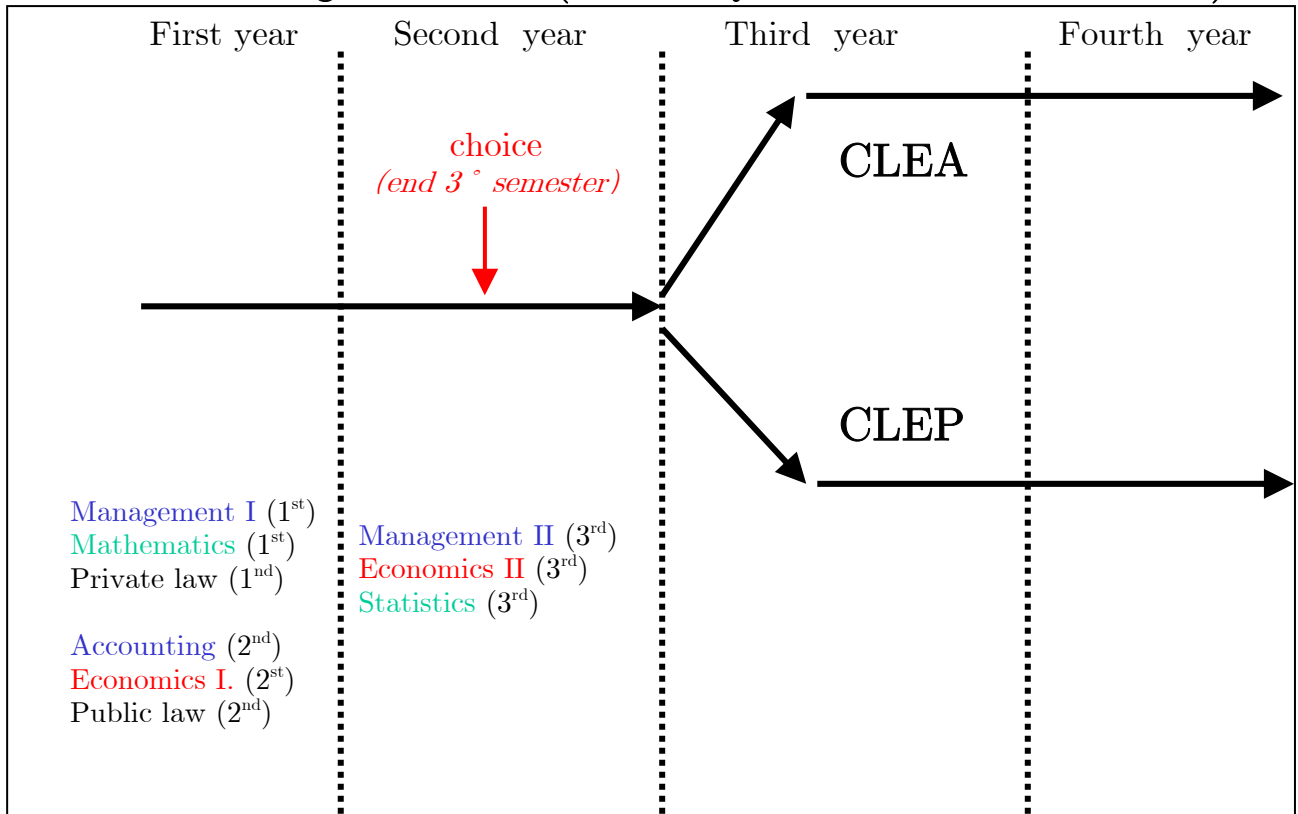


TABLE 1: Common exams CLEA/CLEP

	Semester	Area
Management I (Economia Aziendale)	1 st	Business
Mathematics (Matematica)	1 st	Quantitative
Private Law (Istituzioni di diritto privato)	1 st	Law
Accounting (Metodologie e determinazioni quantitative d'azienda)	2 nd	Business
Economics I (Istituzioni di Economia)	2 nd	Economics
Public Law (Istituzioni di Diritto Pubblico)	2 nd	Law
Economics II (Economia Politica)	3 rd	Economics
Management II (Economia e gestione delle imprese)	3 rd	Business
Statistics (Statistica)	3 rd	Quantitative

TABLE 2: Characteristics of students by degree programme

	High School final grade (0-1)	Admission Test score (0-10)	Admission Test final score (0-100) ¹
CLEA/CLEP	0.86	4.97	68.91
CLELI	0.87	4.84	68.70
CLEFIN	0.89	5.12	72.56
CLAPI	0.89	5.39	71.37
DES	0.90	5.54	71.38
Total	0.87	5.02	69.52

Note:

1. Weighted average of admission test score, high school final grade and average grades in the last 3 years of high school.

Table 3: Descriptive statistics

Variable	Mean	(s.d.)	min	max	Obs.
<i>Individual characteristics</i>					
1=CLEP	0.130	(0.337)	0	1	1122
1=female	0.392	(0.488)	0	1	1122
(log) household income ¹	10.232	(1.348)	-0.7	11.7	872
highest income bracket ¹	0.223	(0.416)	0	1	1122
1=non-resident ²	0.625	(0.484)	0	1	1122
<i>Academic measures</i>					
Graduation mark ³	102.106	(7.705)	76.0	111.0	1030
time to graduation (in years) ⁴	5.342	(0.661)	4.0	7.0	1030
av. grade in all exams	26.174	(2.058)	20.1	30.3	1122
av. grade in common exams	24.818	(2.295)	18.7	30.3	1122
av. grade in quaititative common exams	23.647	(3.091)	18.0	30.5	1122
av. grade in economics common exams	24.687	(2.939)	18.0	31.0	1122
av. grade in business common exams	25.631	(2.506)	18.0	31.0	1122
admission test ⁵	69.079	(7.417)	43.0	91.3	1122
high school final grade ⁶	0.863	(0.112)	0.6	1.0	1122
Number of exams taken on first available :	4.632	(1.992)	0.0	9.0	1122
<i>Characteristics of peers</i> ⁸					
fraction of peers choosing CLEP	0.129	(0.026)	0.1	0.7	1122
av. grade in common exams	24.838	(0.125)	21.8	25.0	1122
av. grade in quaititative common exams	23.671	(0.149)	20.8	23.9	1122
av. grade in economics common exams	24.691	(0.173)	20.5	24.9	1122
av. grade in business common exams	25.652	(0.090)	23.7	26.0	1122
high school final grade ⁶	0.864	(0.004)	0.8	0.9	1122

1. If a student declares that household income falls in the highest income bracket no further information is collected therefore household income is coded to -1 for households in the last bracket and an ad-hoc dummy controls for this group.

2. Resident outside the province of Milan.

3. Range 0-111 (pass = 60).

4. Official duration is 4 years.

5. Normalised between 0 and 100.

6. Normalised between 0 and 1 (pass = 0.6).

7. There are up to 7 available dates in each academic year to sit an exam.

8. Peer groups defined using all 9 common exams.

TABLE 4: Characteristics of CLEA/CLEP students by major

	Obs.	AVERAGE GRADE COMMON EXAMS				High School final grade	Admission Test final score
		Area Business	Area Economics	Area Quantitative	Total		
Total	1122	25.65	24.69	23.67	24.83	.863	69.1
CLEP	146	26.77	26.71	25.76	26.46	.921	72.34
CLEA	976	25.49	24.4	23.36	24.6	.855	68.62
Difference (CLEP-CLEA)		1.28***	2.31***	2.39***	1.86***	.066**	3.71***

Table 5: Characteristics of courses and teaching classes

	Semester	Number of classes	Characteristics	Characteristics			Weight ³ (%)	
				Average	coeff. of variation	Min		Max
Management I	I	10	Enrolled students	140.40	0.11	130	169	0.70
			Student questionnaires	80.70	0.17	62	109	
			Average attendance ¹ (%)	85.67	0.01	84.08	87.24	
			Congestion ² (1 to 5)	3.33	0.05	3.16	3.61	
Mathematics	I	10	Enrolled students	140.80	0.12	125	164	0.55
			Student questionnaires	102.80	0.62	28	253	
			Average attendance ¹ (%)	83.89	0.02	81.39	86.51	
			Congestion ² (1 to 5)	3.77	0.14	3.00	4.57	
Private Law	I	4	Enrolled students	351.75	0.47	189	510	0.78
			Student questionnaires	70.00	0.39	38	104	
			Average attendance ¹ (%)	79.73	0.06	74.91	83.89	
			Congestion ² (1 to 5)	3.07	0.04	2.95	3.23	
Accounting	II	10	Enrolled students	142.80	0.33	109	258	0.57
			Student questionnaires	100.30	0.61	54	215	
			Average attendance ¹ (%)	84.80	0.01	82.26	86.58	
			Congestion ² (1 to 5)	3.46	0.14	3.02	4.40	
Economics I	II	6	Enrolled students	216.50	0.43	85	316	0.52
			Student questionnaires	136.83	0.76	24	317	
			Average attendance ¹ (%)	84.92	0.01	83.56	86.84	
			Congestion ² (1 to 5)	3.63	0.20	2.83	4.82	
Public Law	II	4	Enrolled students	351.75	0.42	217	528	0.83
			Student questionnaires	41.00	0.49	15	64	
			Average attendance ¹ (%)	82.72	0.03	79.45	85.62	
			Congestion ² (1 to 5)	2.89	0.06	2.67	3.03	
Economics II	III	6	Enrolled students	222.83	0.45	156	381	0.67
			Student questionnaires	109.17	0.48	19	176	
			Average attendance ¹ (%)	83.87	0.02	81.42	86.80	
			Congestion ² (1 to 5)	2.96	0.16	2.47	3.72	
Management II	III	8	Enrolled students	184.25	0.56	123	382	1.00
			Student questionnaires	80.75	0.32	56	125	
			Average attendance ¹ (%)	84.38	0.01	83.38	85.27	
			Congestion ² (1 to 5)	2.14	0.12	1.76	2.51	
Statistics	III	8	Enrolled students	272.25	0.33	142	404	0.56
			Student questionnaires	140.75	0.42	35	203	
			Average attendance ¹ (%)	85.66	0.01	83.31	86.53	
			Congestion ² (1 to 5)	3.27	0.29	2.09	4.46	

Notes:

1. Self reported by the students.

2. Congestion is defined from students evaluations as the average answer given to the following question: "For your learning, the number of students attending your class has been: insufficient (1), too low (2), ideal (3), too high (4), excessive (5)".

3. Weight A is the ratio between the lowest maximum level of congestion (i.e. 2.51 for Management II) and the maximum level of congestion across the classes of each course.

TABLE 6: Characteristics of the peer-groups

		Classes weighted by congestion	
		No [1]	Yes [2]
Group size	<i>Mean</i>	889.22	889.22
	<i>St. Dev</i>	80.24	80.24
Within Group Average Nr. of Classes taken together	<i>Mean</i>	1.93	1.38
	<i>St. Dev</i>	.43	.30
Weighted Group size	<i>Mean</i>	188.97	135.54
	<i>St. Dev</i>	24.42	18.61

TABLE 7: Correlation between individual and group averages for selected ability measures

		all 9 common courses [1]	all 9 courses, weighted by congestion ¹ [2]	6 less congestioned courses ¹ [3]	5 less congestioned courses ¹ [4]
Av. Grade	Common Exams	-0.010 (0.739)	-0.013 (0.655)	-0.018 (0.540)	-0.022 (0.453)
Av. Grade	Economics	-0.007 (0.811)	-0.009 (0.769)	-0.007 (0.809)	-0.015 (0.620)
Av. Grade	Business	-0.055* (0.066)	-0.056* (0.061)	-0.047 (0.113)	-0.055* (0.066)
Av. Grade	Quantitative	0.013 (0.662)	0.000 (0.976)	0.027 (0.365)	0.013 (0.662)
High School	final grade	-0.020 (0.506)	-0.020 (0.508)	-0.009 (0.765)	-0.010 (0.736)
Admission	test	-0.033 (0.275)	-0.036 (0.233)	-0.030 (0.320)	-0.035 (0.242)
Number of exams	taken on first available session ²	0.055* (0.065)	0.064** (0.032)	0.056* (0.062)	0.057* (0.056)

1. Congestion is defined from students evaluations as the average answer given to the following question: "For your learning, the number of students attending your class has been: insufficient (1), too low (2), ideal (3), too high (4), excessive (5)". In column [3] Mathematics, Management II and Economics II are excluded from the construction of the peer groups. In column [4] also Statistics is excluded. See Table 5 and text for details.

2. There are up to 7 available dates in each academic year to sit an exam.

Significance levels in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 8: Peer-effects in subject choice

Dependent variable: Probability of choosing CLEP				
Peer groups defined using:	all 9 common courses	all 9 common courses, weighted by congestion ¹	6 less congested ¹ courses	5 less congested ¹ courses
	[1]	[2]	[3]	[4]
Fraction Peers choosing CLEP	0.532** (0.245)	0.521** (0.246)	0.468* (0.254)	0.507** (0.245)
Av.gr.Economics/av.gr.Business	0.431*** (0.096)	0.431*** (0.096)	0.431*** (0.096)	0.431*** (0.096)
<i>Ability measures</i>				
Av.Grade Common Exams	0.020*** (0.008)	0.020*** (0.008)	0.020*** (0.008)	0.020*** (0.008)
Av.Grade Quantitative Exams	0.007 (0.005)	0.007 (0.005)	0.007 (0.005)	0.007 (0.005)
Admission test ²	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
High school final grade ³	0.191* (0.110)	0.191* (0.110)	0.191* (0.110)	0.191* (0.110)
Number of exams taken on first available session ⁴	-0.004 (0.005)	-0.004 (0.005)	-0.003 (0.005)	-0.003 (0.005)
High school type dummies	yes	yes	yes	yes
<i>Individual characteristics</i>				
1=female	-0.004 (0.018)	-0.004 (0.018)	-0.004 (0.018)	-0.004 (0.018)
Household income ⁵	0.006 (0.008)	0.006 (0.008)	0.006 (0.008)	0.006 (0.008)
1=highest income bracket ⁵	0.056 (0.125)	0.056 (0.124)	0.054 (0.124)	0.056 (0.124)
1=non resident ⁶	0.000 (0.026)	0.000 (0.026)	0.000 (0.026)	0.000 (0.026)
Region of residence dummies	yes	yes	yes	yes
Nr. Observations	1122	1122	1122	1122
Pseudo R-squared	0.19	0.19	0.19	0.19

Note:

1. Congestion is defined from students evaluations as the average answer given to the following question: “For your learning, the number of students attending your class has been: insufficient (1), too low (2), ideal (3), too high (4), excessive (5)”. In column [3] Mathematics, Management II and Economics II are excluded from the construction of the peer groups. In column [4] also Statistics is excluded. See Table 5 and text for details.

2. Normalised between 0 and 100. Average in the sample = 69.10

3. Normalised between 0 and 1 (pass = 0.6). Average in the sample = 0.863

4. There are up to 7 available dates in each academic year to sit an exam.

5. If a student declares that household income falls in the highest income bracket no further information is collected therefore household income is coded to -1 for households in the last bracket and an ad-hoc dummy controls for this group.

6. Resident outside the province of Milan.

The numbers reported represents marginal effects for the average student in the sample.

Robust standard errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 9: Distribution of decision modes

		ABILITY INFLUENCE	
		YES ($g > 1$)	NO ($g < 1$)
PEERS' INFLUENCE	YES ($f > 1$)	Coherent 34.40%	Peer driven 18.55%
	NO ($f < 1$)	Ability driven 29.37%	Incoherent 17.68%

TABLE 10: Decision modes and academic outcomes

Dependent variable:	Av. Grade in non-common exams ¹		Graduation mark ²		Time to graduation ³ (in years)
	[1]	[2]	[3]	[4]	[5]
<i>Decision mode</i>					
Peer driven	-0.186** (0.090)	-0.157* (0.086)	-0.678** (0.307)	-0.602** (0.299)	0.048 (0.054)
Coherent	-0.110 (0.080)	-0.156** (0.077)	-0.266 (0.267)	-0.386 (0.262)	-0.106** (0.047)
Incoherent	-0.246** (0.096)	-0.217** (0.091)	-0.637* (0.328)	-0.561* (0.318)	0.036 (0.059)
<i>Ability measures</i>					
Av. grade all exams	-	-	-	-	-0.167*** (0.014)
Av. grade common exams	0.641*** (0.020)	0.592*** (0.020)	2.867*** (0.069)	2.740*** (0.070)	-
Time to graduation	-	-0.488*** (0.054)	-	-1.271*** (0.181)	-
1=CLEP	-0.212** (0.086)	-0.190** (0.085)	-0.024 (0.316)	0.034 (0.317)	0.041 (0.056)
Admission test ⁴	0.006 (0.005)	0.006 (0.005)	-0.018 (0.016)	-0.020 (0.016)	0.002 (0.003)
High school final grade ⁵	2.554*** (0.449)	2.432*** (0.425)	7.587*** (1.541)	7.271*** (1.495)	0.300 (0.253)
High school type dummies	yes	yes	yes	yes	yes
<i>Individual characteristics</i>					
1=female	0.348*** (0.066)	0.277*** (0.064)	1.059*** (0.222)	0.874*** (0.220)	-0.104*** (0.039)
Household income ⁶	-0.015 (0.031)	-0.022 (0.027)	-0.062 (0.110)	-0.078 (0.098)	-0.015 (0.015)
1=highest income bracket ⁶	-0.088 (0.365)	-0.226 (0.320)	-0.564 (1.288)	-0.925 (1.156)	-0.296 (0.182)
1=non resident ⁷	0.119 (0.095)	0.121 (0.090)	0.379 (0.319)	0.385 (0.306)	0.016 (0.056)
Region of residence dummies	yes	yes	yes	yes	yes
Nr. Observations	1030	1030	1030	1030	1030
R-squared	0.74	0.76	0.82	0.83	0.24

Note:

1. Range 0-30 (18 = pass). Average in the sample = 26.97
 2. Range 0-111 (pass = 66). Average in the sample = 102.11
 3. Official duration is 4 years. Average in the sample = 5.34
 4. Normalised between 0 and 100. Average in the sample = 69.10
 5. Normalised between 0 and 1 (pass = 0.6). Average in the sample = 0.863
 6. If a student declares that household income falls in the highest income bracket no further information is collected therefore household income is coded to -1 for households in the last bracket and an ad-hoc dummy controls for this group.
 7. Resident outside the province of Milan.
- Robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 11: Interval wage regressions

Dependent variable:	wage in the first job ¹	
	[1]	[2]
graduation mark ²	6.045*** (1.360)	3.718** (1.612)
1=full marks ³		66.881*** (25.013)
time to graduation ⁴	-2.450* (1.443)	-2.279 (1.443)
1=female	-97.039*** (17.360)	-94.362*** (17.368)
Household income ⁵	-0.000 (0.000)	-0.000 (0.000)
1=highest income bracket ⁵	-2.276 (26.449)	-3.612 (26.428)
1=post-graduate studies	-19.498 (19.099)	-18.686 (19.078)
High school final grade ⁶	-109.330 (89.325)	-121.373 (89.369)
High school type dummies	yes	yes
Degree programme dummies	yes	yes
Contract type dummies	yes	yes
Observations	3982	3982

1. Recorded in intervals

2. Range 0-111 (pass = 66).

3. 110 with or without honours

4. Recorded in quarters. Official duration is 4 years.

5. If a student declares that household income falls in the highest income bracket no further information is collected therefore household income is coded to -1 for households in the last bracket and an ad-hoc dummy controls for this group.

6. Normalised between 0 and 1 (pass = 0.6).

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.1: Characteristics of the teaching classes

Course name	Semester	Class number	Enrolled students	Number of completed student questionnaires	[5]/[4]	Attendance ¹ (%)	Congestion ² (1 to 5)
[1]	[2]	[3]	[4]	[5]	[6]	[8]	[7]
Management	I	1	169	109	0.64	86.28	3.61
Management	I	2	130	62	0.48	84.11	3.19
Management	I	3	131	67	0.51	87.23	3.27
Management	I	4	134	80	0.60	85.78	3.40
Management	I	5	133	68	0.51	87.24	3.51
Management	I	6	135	92	0.68	84.84	3.18
Management	I	7	134	77	0.57	85.70	3.21
Management	I	8	134	81	0.60	86.19	3.33
Management	I	9	136	85	0.63	84.08	3.39
Management	I	10	168	86	0.51	85.29	3.16
Average			140.40	80.70	0.57	85.67	3.33
Coeff. of variation			0.11	0.17	0.12	0.01	0.05
Mathematics I	I	1	160	147	0.92	83.56	4.18
Mathematics I	I	2	156	87	0.56	84.72	4.21
Mathematics I	I	3	125	35	0.28	83.30	3.00
Mathematics I	I	4	127	92	0.72	83.57	3.82
Mathematics I	I	5	128	109	0.85	82.81	4.15
Mathematics I	I	6	164	119	0.73	85.46	3.80
Mathematics I	I	7	128	69	0.54	86.51	3.35
Mathematics I	I	8	128	89	0.70	85.01	3.56
Mathematics I	I	9	131	28	0.21	81.39	3.11
Mathematics I	I	10	161	253	1.57	82.53	4.57
Average			140.80	102.80	0.71	83.89	3.77
Coeff. of variation			0.12	0.62	0.53	0.02	0.14
Private Law	I	1	510	104	0.20	83.89	3.23
Private Law	I	2	475	71	0.15	74.91	3.00
Private Law	I	3	233	67	0.29	83.27	3.12
Private Law	I	4	189	38	0.20	76.84	2.95
Average			351.75	70.00	0.21	79.73	3.07
Coeff. of variation			0.47	0.39	0.27	0.06	0.04
Accounting	II	1	258	215	0.83	82.26	4.08
Accounting	II	2	144	55	0.38	84.05	3.07
Accounting	II	3	164	83	0.51	84.11	3.24
Accounting	II	4	178	211	1.19	83.81	4.40
Accounting	II	5	136	54	0.40	85.22	3.02
Accounting	II	6	110	98	0.89	85.47	3.60
Accounting	II	7	110	57	0.52	85.06	3.02
Accounting	II	8	110	88	0.80	86.58	3.72
Accounting	II	9	109	74	0.68	86.01	3.31
Accounting	II	10	109	68	0.62	85.43	3.12
Average			142.80	100.30	0.68	84.80	3.46
Coeff. of variation			0.33	0.61	0.37	0.01	0.14
Economics I	II	1	280	111	0.40	86.84	3.87
Economics I	II	2	290	175	0.60	83.56	3.84
Economics I	II	3	316	317	1.00	84.78	4.82
Economics I	II	4	85	24	0.28	85.92	2.83
Economics I	II	5	184	138	0.75	84.31	3.40

Economics I	II	6	144	56	0.39	84.12	3.02
Average			216.50	136.83	0.57	84.92	3.63
Coeff. of variation			0.43	0.76	0.47	0.01	0.20
Public Law	II	1	528	44	0.08	82.65	2.89
Public Law	II	2	419	41	0.10	79.45	2.97
Public Law	II	3	243	15	0.06	83.17	2.67
Public Law	II	4	217	64	0.29	85.62	3.03
Average			351.75	41.00	0.13	82.72	2.89
Coeff. of variation			0.42	0.49	0.80	0.03	0.06
Economics II	III	1	160	110	0.69	84.14	3.33
Economics II	III	2	315	176	0.56	83.95	3.72
Economics II	III	3	381	142	0.37	84.92	2.91
Economics II	III	4	156	19	0.12	81.42	2.47
Economics II	III	5	163	106	0.65	86.80	2.73
Economics II	III	6	162	102	0.63	81.99	2.61
Average			222.83	109.17	0.50	83.87	2.96
Coeff. of variation			0.45	0.48	0.43	0.02	0.16
Management II	III	1	319	113	0.35	84.84	2.51
Management II	III	2	382	125	0.33	84.48	2.43
Management II	III	3	123	66	0.54	83.38	2.28
Management II	III	4	125	61	0.49	84.12	1.97
Management II	III	5	133	56	0.42	84.30	1.98
Management II	III	6	133	91	0.68	84.91	1.76
Management II	III	7	125	65	0.52	85.27	2.11
Management II	III	8	134	69	0.51	83.70	2.07
Average			184.25	80.75	0.48	84.38	2.14
Coeff. of variation			0.56	0.32	0.24	0.01	0.12
Statistics	III	1	370	157	0.42	83.31	3.54
Statistics	III	2	142	35	0.25	86.53	2.09
Statistics	III	3	404	203	0.50	86.09	2.86
Statistics	III	4	240	172	0.72	85.97	4.27
Statistics	III	5	248	157	0.63	86.21	4.02
Statistics	III	6	192	64	0.33	85.66	2.24
Statistics	III	7	336	180	0.54	85.18	2.65
Statistics	III	8	246	158	0.64	86.36	4.46
Average			272.25	140.75	0.50	85.66	3.27
Coeff. of variation			0.33	0.42	0.32	0.01	0.29

Note:

1. Self reported by the students.

2. Congestion is defined from students evaluations as the average answer given to the following question: *“For your learning, the number of students attending your class has been: insufficient (1), too low (2), ideal (3), too high (4), excessive (5)”*.