Does class-size affect the academic performance of college freshers?*

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1 Introduction

The influence of class size in academic performance has been the focus of both academic and policy debate. Obtaining credible estimates of the impact of class size on performance is challenging because both performance and class size vary with other common variables like students' background. In the last 10 years, researchers focused on settings where a clear and credible identification strategy for the influence of class size on academic performance is available. Examples are Krueger (1999) and Barnejee *et al.* (2005) that exploit randomized experiments conducted in Tenesse (US) and in Mumbai (India) respectively. Maximum class size rules have been exploited by Angrist and Lavy (1999), Hoxby (2000), and Urquiola (2006) using data from Israel, Connecticut (US), and Bolivia respectively.

In this paper, we investigate how class size influence academic performance in college. Most of the previous literature on the effect of class size on performace has focused on primary and secondary school, and very little attention has been given to college. Except for Martins and Walker (2006), we are not aware of any other paper that investigates the relation between college class size and academic achievement. Clearly, the existing evidence from primary and secondary school cannot be extrapolated to college. The results of our research will be interesting

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for policy makers that must decide on college funding, college administrators that must decide on the number of classes, and students that have to choose among colleges with different student/teacher ratios.

We use administrative data from Universidad Carlos III de Madrid because it offer us an extremely valuable and unique identification strategy. fresher have to enroll in a set of core subjects in the first year. Because of the large number of students, there are several classes for the same subjects. The way that different students are allocated to the different classes is particularly interesting for our identification strategy. fresher are allocated to different classes according to the first letter of their surname. The cut-off letters are not decided once the number of students and their distribution is known, but they are fixed a priori and have hardly been changed in the last 5 years. These allocation mechanisms generate a different number of fresher in each class, being the first letter of their surname what dictates their allocation to a particular class. Our identification assumption will be that the first letter of the surname does not contain information about the student's ability. Consistent with that, we will show that the number of fresher students in each class is uncorrelated with the grade of the entry exam to university.

It is worth emphasizing a few institutional details. In Universidad Carlos III de Madrid, as in most Spanish universities, students have both lectures and tutorials, which are usually dedicated to solve exercises. The class comprises both lectures and tutorials. Hence, it is different from the UK where students attending the same lecture are divided into several smaller tutorial classes. In our setting, the class size is both the class of the lecture and the tutorial.

2 The allocation of students to classes

Here, we will describe the allocation of students to classes of courses of the first year of the degree.[1] Due to the large number of students in the university, students of the same degree are allocated to different groups. Students in the same group have the same core courses, timetables, and lecturers. Students of different groups will have the same core courses, but they might have different timetables and lecturers. A class is a year-group-course combination.

The rules used to allocate fresher to groups are different from the ones to allocate repeat students or visiting students. The university administration uses a strict alphabetic rule to allocate fresher students in groups. fresher students are assigned to a group based on their surname and cannot change groups.[2] Table 1 shows the surname cuttoff letters used to determined which students are included in which groups over the years for two degrees that we analyze: Business and Business&Law. fresher students must compulsory enroll in all the

[1] By courses, we mean subjects in the degree such as Microeconomics I, or Mathemathics for Economist I.

[2] There are few exceptions to this rule where for reasons of health or important activities freshmen may request a change of schedule for particular classes. All the requests have to be addressed to the vice-dean. In our data only 29 freshmen belong to more than 1 group.

core courses of the first year.

Repetitors of a particular course (students that did not pass the exam for that course in the previous year) enroll in the course that they did not pass the previous year, and in the second year courses of their choice. Regarding their first year courses, the university administration will initially allocate to them the group according to the alphabetical rule used for fresher students. However, if there is any schedule incompatibility between their first year course and their second year ones, then the repeat student can choose the group for his first year course(s), overriding the alphabetic rule. Visiting students, who represent only a small fraction of the total number of students, can also choose the group, and their allocation to groups do not follow the alphabetical rule.

If all students were fresher, a group would be a set of students who take exactly the same courses and all classes taken by that group would have the same size. However, class size vary by subject, even within the same group, because repeat and visiting students do not enroll in all the first year courses.

Business (Getafe campus)					
Group	2000-2001	2001-2002	2002-2003	2004-2005	2005-2006
71		A-E	A-E	A-E	A-E
72		F-K	F-L	F-L	F-L
73		L-P	M-P	M-P	M-P
74		Q-Z	Q-Z	Q-Z	Q-Z
75 (english)	students may select to be in the bilingual group				
Business-Law (Getafe campus)					
17/77		A-GA	A-K	A-K	A-K
18/78		GB-M	L-Z	L-Z	L-Z
19/79		N-Z			

Table 1: Distribution of Surnames by Group and year

Both the class and group size have an exogenously determined component made of fresher that cannot choose group and a potential endogenous component made of repeat and visiting students. Our identification strategy will use the number of fresher students in a group as an instrument for class size. We will be assuming that the number of fresher students in a group is orthogonal to student's background given that the allocation of fresher students to a group is just determined by the first or the two first letters of the surname. Below, we will show that the number of fresher students in a group is not correlated with the grade in the entry exam to university. This will give strong support to our identification assumption.

3 The Data

We have data from students enrolled in first-year courses of Business and of Business&Law at the Universidad Carlos III de Madrid (Spain) from academic

year $2000-2001$ to $2004-2005$. The academic year at this university consists of two semestres (fall and spring) and three exam episodes. For each course there are two exam calls a year. Exams corresponding to fall semestre courses take place in February and September. Exams corresponding to spring semestre courses take place in June and September. If a student fails to pass a subject during the academic year, i.e. missing the exam or failing in both the first call (February/June) and the September call, then the student has to repeat the course in the following academic year. Students have up to four opportunities or calls to pass an exam. A student who fails to pass an exam after four calls must leave the university.

Our data consist on all the exam information, including grades, for each student until passing each course. Hence, in our data each student-subject may correspond to a single observation, i.e. if the student passes the course in the first call, or up to four observations. We also know if the student misses an exam call. We compute class size for a course-group combination by adding up the students that either took or missed the exam of that course-group combination. These will include fresher, repeat, visitor students, as well as some students with degrees obtained abroad that need to take some courses at the univerisity in order to their degree be recognized in Spain.

We study the degrees of Business and Business&Law. Each of these degrees are offered in two different campus located in the suburbs of the Spanish capital. Students can choose between the main campus of the university (Getafe) or a smaller one (Colmenarejo). We restrict our analysis to those students that choose the campus of Getafe because there is only one group in the Colmenarejo campus. We perform separate analysis for Business and for Business&Law due to the clear selection of students into Business&Law.[3] Students of the Business degree can choose a group where the lectures are given in English. We also exclude it from the analysis.

Our clean data has 37702 observations, corresponding to 2683 students, of which 1978 are registered in the Business program and 732 in Business&Law [4]. Only 311 belong to the Bilingual group which is taught in English. We will not use this group in our analysis. Our data comprises 37 groups-year combinations, 12 of them correspond to Business&Law, 5 of them to the Business degree taught in English, 20 the regular Business program. There are a total of 15 different courses, 10 of which are taught in the Business program and 12 are taught in the Business&Law program.

A class is a year-group-course combination. Class sizes vary by subject because repeat and visiting students do not enroll in the courses. There are 200 classes in the Business degree (20 groups times 10 courses), and 144 in the Business&Law program (12 groups times 12 courses). The class size statistics

[3] Business is a four-year regular bachelor program while Business&Law is a six-year program. Unsurprisingly, the average student that enrolls in the Business&Law program has better academic background than those that enroll in the Business degree. This can be seen by the difference in the mean and minimum access grades of both programs.

[4] Note that there are 27 students that belong to both Buesiness and Business&Law. These students tipically start in one program and ask for change of programs in the following year.

are given in Table 2. Figure 1 shows that there is substantial variation even within each year.

Table 2. Class size statistics

	Business	Business & Law
Min	49	36
10 percentile	67	38
25 percentile	74	48
Median	82	63
75 percentile	90	69
90 percentile	96	74
Max	129	113
Mean	82.2	58.4
Standard dev	12.5	14.1

4 Empirical estrategy

4.1 Instrument validity

Estimating the casual relation between class size and education achievement is challenging because class size can potentially be correlated with student's ability. In this paper, we take advantage of the alphabetical rule that the administration of the university follows to allocate fresher students to groups. As we have mentioned, class size is the sum of fresher, repeat and visiting students. The allocation of freshert students to different groups (and hence to different classes) is done according to their first letter of the surname, using the rule stated above. We believe that the first letter of the surname does not contain any information about the student's ability. In order to support our claim, we will study the relation between the number of fresher students in a group and previous educational achievement.

In order to entry into a Spanish university, students have to pass an exam. The exam is the same in each region of the country. The exam is comprenhensive and it is done in two or three days. It includes a test of English, Reading Comprenhension, Spanish Language, and four more topics of the student's choice. Students that are going to study Business generally include maths in their choice. Other possible choices are chemistry, physics, geology, biology, latin, literature, and history. The grade obtained in this exam is averaged with the average grade that they have obtained in the last three years of high school, yielding the *grade to enter university.* This is a score between 5 and 10. This score is very important for students because college admissions are rationed using this score Table 3 gives the distribution of the *grade to enter university.*

Table 3. Distribution of fresher's grade to enter university and group sie

	Distribution of fresher's grades	
	Business	Business & Law
Min	5.38	5.4
10 percentile	6.24	7.25
25 percentile	6.40	7.44
Median	6.76	7.86
75 percentile	7.27	8.4
90 percentile	7.92	8.83
Maximum	9.62	9.66
Mean	6.92	7.94
Standard deviation	0.66	0.62

Figures 2 and 3 show the scatterplot of average grade to enter university among fresher in each group and the number of fresher in each group (our instrument). According to these graphs, there is no apparent relation between these two variables. Table 4 shows the results of the regressions that correspong with Figures 2 and 3. The regressions are done at the year-group level. The dependent variable is the average grade to enter university in each year-group combination. This table confirms the interpretation from the previous graphs: we cannot find a relation between fresher's grades to enter university and the number of fresher in the group. Notice that, given the dispersion in the variable number of freshers, the relation is accurately estimated despite the small number of year-groups.[5] For instance, the effect of the number of fresher in the average entering grade for Business would have been siginificant if the estimate was -0.0032, and not -0.0016. However, -0.0032 still would have implied a weak relation between number of freshers and average entering grade (-0.0032 would have implied that the average entering grade decreases in 0.032 if the number of fresher students increases by 10. A decrease of 0.032 in the average grade would have meant just a 5% of the standard deviation of the entering grade distribution as reported in Table 3).

Table 4: Regressions of entering grade over number of fresher in the group

	Average entering grade	
	Business	Business&Law
Constant	7.01	7.97178
	(0.13)	(.13531)
Number of freshers	-0.0016	0.0006
	(0.0016)	(0.0012)
Number of year-groups	20	12

The regressions are done at the year-group level.
The regressions controls for year dummies

Table 5 shows the same regressions than before but at the individual level. The standard errors are clustered at the year-group level. We obtain the same picture as before, that is, the number of freshers in a group is not correlated with the student's grade to enter university.

[5] The standard deviation of the difference between the number of freshers in a group and the year average is 8.8 for the business degree, and 8.23 for the the business & law degree.

Table 5: Regressions of entering grade over number of fresher in the group

	Business	Business&Law
Constant	6.87	7.70
	(0.09)	(0.08)
Number of fresher	-0.0008	0.0004
	(0.0015)	(0.0012)
Female dummy	0.111	0.079
	(0.038)	(0.038)
Number of individuals	1484	643
Number of year-groups	20	12

The regression controls for time dummies

Standard errors, computed using bootstrap, are clustered at the year-group level

According to the above results, there is no relation between past educational achievement (as measured by the grade to enter university) and the number of freshers in the group. Consequently, we cannot reject that our instrument, the number of frehers in a group, is valid.

4.2 Econometric modelling

Our basic econometric strategy will consist of estimating a variable that measure current educational achievement over class size, year dummies, and course dummies. Our econometric model will be:

$$y_{tgci} = f(\sum_{t=1}^{5} yd_t\alpha_t + \sum_{c=1}^{nc} cd_c\beta_c + X_i\gamma + CS_{tgc}\delta + \varepsilon_{tgci}), where \quad (1)$$

y_{tgci} = measure of educ achievement for student i in course c that is part of group g in year t

yd_t = year dummy for year t

cd_c = course dummies (dummies for maths, microeconomics...)

X_i = variables that vary at the individual level (such as gender)

CS_{tgc} = class size for course c that is part of group g in year t

nc = number of courses in the degree

Class size could be endogenous because repeat students have certain freedom to choose the class that they want to attend. For instance, classes that are relatively large could be classes that are particularly attractive to repeat students. This could accentuate the effect of class size on educational achievement as repeat students will generally have worse academic background. Consequently, we will consider that class size is potentially endogenous, and we will instrument it using the number of freshers in the group to which the class belongs to. We justified our instrument in the previous section.

For our estimating sample, we will only consider freshers. This is advisable for several reasons. First, we cannot rule out that a fresher student chooses the class on the basis of the number of freshers in the group. Though, repeat students will generally have not access to this information, they could learn it

from past experience. Second, it is unclear whether the appropiate treatment variable for them is the class size in the year that we observe them, or in the previous years in which they have not been able to pass the exam.

We cluster the standard errors at the group level. This will take into account of intra-group correlation. Intra-group correlation will emerge either because individuals in the same group can suffer similar shocks, or because the same individual appears several times in the estimating sample. This happens because we pool all the courses. Existing formulas for computing clustered standard error apply asymptotic theory and hence they assume that the number of clusters tends to infinity. Given that our number of clusters is not large, we bootstrap the standard errors. We use 500 replications.

As we mentioned before, students have two calls a year for each exam. Independently of whether they miss the exam call or not, the students must pass the course in the first four exam calls. Otherwise, they might be expelled from the university. Students can decide to miss an exam call. This is not completely uncommon. For intance, 8.8% of freshers of the business degree and 6.05% of freshers of the Business&Law degree missed the first exam call. Students will generally miss an exam if they know that they have not studied enough to pass it. They might even decide to focus all their attention in the exam of a few courses, and leave the rest of courses for the second call. A missed exam is a problem for the econometrician because it means that the educational achievement is not observed. For those students that sit in a exam, we observe the exam score that is a number between 0 and 10. An exam is considered passed if the exam score is 5 o larger.

We will consider two measures of educational achievement: *pass* and *grade* as outcome variables. The variable *pass* takes value 1 if the student has passed the exam, and 0 if the student has failed the exam, or if it has missed it. Failing an exam is not uncommon. 31.2% of freshers of the business degree and 23.71% of freshers of the business&law degree failed their exam in the first call. The variable *grade* takes a the value of the exam score if the student passed the exam. For those students that failed or missed the exam, we will assume that their score exam was lower than 5.[6] We will consider $pass1$, $pass2$, $grade1$,and $grade2$. The variables $pass1$ and $grade1$ are built with the results of the first exam call. The variables $pass2$ and $grade2$ will have the value of the first exam call if the student passed in the first exam call, and will have the value got in the second exam call if they fallied or missed the first exam call. We will not consider further calls because students are considered repeat students if they do not pass after the first two exam calls.

Assuming that an student got a score of less than 5 when he did not sit in the exam could be problematic if, at the moment of the exam, students knew enough so at to pass the exam but they prefered not sit in order to get a better mark in the following call. Though we do not believe that this strategy is particularly prevalent for students in their first exam call, we cannot rule

[6] In the future we plan to develop a model that assigned the exam score to all those individuals that sat in the exam, indepedently of whether they passed or not, and a score of less than 5 if they did not sit in the exam.

it out.[7]Consequently, we will interpret our results for $pass1$ and $grade1$ with caution.[8] However, the strategy mentioned above does not seem realistic for students in their second exam call because if they do not pass the second exam call then they will become repeat students, they will have to pay the fee of the course for the next year, and both the syllabus of the course and lecturer could change. Moreover, their degree certification will show that the number of calls that they used to pass the exam. Consequently, we feel confident with our results on the variables $pass2$ and $grade2$. Moreover, we do not think that the problem is so important because the percentage of observations with missed outcomes is not that large (between 8% and 6% for the first call).

Following Angrist(1991), we will use a linear probability model to estimate the models that have $pass1$ and $pass2$ as dependent variables.[9] For $grade1$ and $grade2$,we will use a tobit model that accomodates a continuos endogenous regressor. Basic statistics for the distribution of $grade1$ and $grade2$ are given in Table 6.

Table 6, Basic statistics for outcome variables.

	Business		Business&Law	
	Mean	SD	Mean	SD
$Grade1$	6.59	1.36	6.73	1.39
$Grade2$	6.47	1.32	6.64	1.37
$Pass1$	0.60	0.49	0.70	0.45
$Pass2$	0.76	0.42	0.86	0.86

5 Results

As we have justified before, we will use the number of freshers in the group in a given year to instrument for the class size A class is a combination of year-group-course. Class size varies by course because visiting and repeat students do not enroll in all the courses. There are 200 classes in the Business degree (20 groups times 10 courses), and 144 in the Business&Law program (12 groups times 12 courses). The number of freshers in a group in a given year is constant across courses because freshers have to enroll in all the courses. Clearly, the number of freshers in a group in a given year will very correlated with class size because freshers are a large proportion of a class. Table 7 below shows the first stage regresion, that is, the regression of class size over the number of freshers and other covariates. Clearly, the number of freshmen is a very good predictor of class size, and hence we do not a problem of weak instruments.

[7]For the Business degree, out of those students that missed the first exam call, 73.4% also missed the second exam call, 12.2% failed the second exam call, and only 3.29% obtained a score higher than 7 that implies a certain degree of recognition above the "pass". Consequently, it does not seem that most of students that missed the first exam call knew enough so as to pass on the second one.

[8]In the future, we plan to test the robustness of our assumption by assuming that those that missed the exam could have got a grade of less than 7 or 8, instead of 5.

[9]In the future, we plan to use a probit model that accomodates a continuous endogenous variable.

Table 7, First Stage Regression. Dependent vble: class size.

	Business	Business&Law
Number of freshmen	0.933	0.93
	(0.22)	(0.20)
Female	0.16	0.07
	(0.15)	(0.06)
Grade to enter university	0.05	0.087
	(0.10)	(0.048)
N. individuals	13943	13976
N. clusters	20	12
N. classes	200	144

Include subject, lecturers category, and year dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

Table 8 and 9 shows the results for our outcome equation, but assuming the class size is exogenous. We do not find any statistically significant impact of class size on our measures of educational achievement. Notice how the variable "Grade to enter university", that is, our measure of past educational achievement, is a strong predictor of education achievement during the first year of the degree. These results could be biased because relatively large classes could be those for which repeat students have a preference. Although we do not use repeat students in the estimation sample, they could constitute an externality for the freshers.

Table 8, Results of basic specification (assuming exogeneity of class size)

	Business			
	Pass1	Pass2	Grade1	Grade2
$\frac{CS}{100}$	0.06	0.03	0.61	0.44
	(0.09)	(0.03)	(0.37)	(0.33)
Female	0.01	0.03	-0.09	-0.06
	(0.01)	(0.01)	(0.08)	(0.06)
Grade to enter university	0.21	0.16	1.28	1.07
	(0.008)	(0.005)	(0.42)	(0.04)
N individuals	13943	13976	13985	14057
N. clusters	20	20	20	20

Include subject and year dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

Table 9: Results of basic specification (assuming exogeneity of class size)

	Business & Law			
	Pass1	Pass2	Grade1	Grade2
$\frac{CS}{100}$	-0.157	-0.062	-1.517	-1.060
	(0.158)	(0.086)	(0.924)	(0.899)
Female	-0.154	0.009	-0.113	-0.059
	(1.88)	(0.010)	(0.074)	(0.048)
Grade to enter	.206	0.136	1.307	1.049
university	(.012)	(0.011)	(0.063)	(0.044)
N indiv.	7649	7663	7659	7687
N. clusters	12	12	12	12

Include subject and year dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

Table 10 and 11 show the estimates of the outcome equations using the number of freshmen as an intrument for class size. The estimations show that "grade to enter university" has a postive and significant impact on our outcome measures. However, the estimate of class size on the outcome measures are negative for the Business&Law degree and positive for the Business degree, neither of them statistically different from zero. More importantly, notice that our point estimates are quite small. An increase of one standard deviation in class size would change the probability of passing the exam in 0.027 and 0.017 in the first and second call respectively for the business degree, -0.023 and -0.008.[10] Regarding $grade1$ and $grade2$, an increase of one standard deviation in class size would change $grade1$ and $grade2$ in $0,126$ and 0.08 that constitute a 9.2% and 6% of the standard deviation of the variable for the business degree. For the business&law degree, the increase in $grade1$ and $grade2$ would be of 0.287 (20.6% of a standard deviation for $grade1$) and 0.25 (18.2% of a standard deviation of grade2) respectively.

Table 10, Results of basic specification (instrumental variables)

	Business			
	Pass1	Pass2	Grade1	Grade2
$\frac{CS}{100}$	0.217	0.14	1.01	0.64
	(0.135)	(0.14)	(0.67)	(0.50)
Female	0.016	0.03	-0.087	-0.06
	(0.013)	(0.016)	(0.079)	(0.067)
Grade to enter	0.21	0.16	1.286	1.075
university	(0.008)	(0.74)	(0.045)	(0.037)
N indiv.	13943	13976	13985	14057
N. clusters	20	20	20	20

Include subject and year dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

Table 11: Results of basic specification (instrumental variables)

[10] The standard deviation of class size for business is 12.5. $(12.5)/100 * 0.217 = 0.027$; $(12.5)/100 * 0.14 = 0.017$. A standard deviation of class size for business&law is 14.1. $(14.1)/100 * -0.162 = -0.023$;
$(14.1)/100 * -0.055 = -0.008$

	Business & Law			
	Pass1	Pass2	Grade1	Grade2
$\frac{CS}{100}$	-0.162	-0.055	-2.04	-1.764
	(3.62)	(1.058)	(2.29)	(2.42)
Female	-.001	0.009	-0.118	-0.065
	(0.019)	(0.011)	(0.075)	(0.046)
Grade to enter	0.200	0.136	1.308	1.05
university	(0.012)	(0.012)	(0.065)	(0.039)
N indiv.	7649	7663	7659	7687
N. clusters	12	12	12	12

Include subject and year dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

Our estimates of class size could still be biased depending on how lecturers are allocated to classes. There are three dimensions that we can think of regarding how lecturers will choose classes: course, class size, and timetable. The above estimations control for course. We investigate the remaining two below. Table 12 reports how class size varies with the category of the lecturer.

Table 12 reports the results of a regression of class size over different categories of lecturers, ranging from Professor (the reference category) to Instructor.[11] These estimates show that the average class sizes do not vary by the category of the lecturer. However, lecturers must have some criteria to choose among different classes ,apart from the choosing the course they are going to teach. Table 13 shows the proportions of various lecturer types that teach on some chosen days (Monday and Thursday). The table 13 shows that the allocation of teachers to days is not random. The proportions of instructors teaching on a Monday is high, while the proportions of associate and assistants teaching on a Thursday is also particularly high. The allocation of lecturers to different times also does not appear to be random. For example, assistant or associate professors are more frequently observed to teach early morning classes, whereas instructors are the most likely to teach after 1:00 pm.

Table 12: Estimates of class size over lecturer category

[11] The percentage of unknown is a 19%

	Business	Business&Law
Constant	78.07	53.76
	(6.24)	(4.81)
Instructor4	0.31	0.25
	(5.16)	(3.80)
Assistant5	-1.19	-3.49
	(5.71)	(6.34)
Associate6	0.38	1.17
	(5.84)	(3.64)
Other7	-1.81	-9.51
	(7.13)	(8.13)
Unknown3	-0.53	-0.51
	(5.39)	(3.91)
Number of classes	200	144

The default category is Professor

The regression also includes time and course dummies

Table 13: Estimates of class size over lecturer category

	Business		Business&Law	
	Monday	Thursday	Monday	Thursday
Professor	83%	17%	42%	50%
Instructor	56%	41%	53%	49%
Assistant	30%	55%	50%	50%
Associate	34%	75%	50%	63%
Other	33%	67%	50%	100%
Unknown	50%	39%	59%	59%
Number of classes	200	200	144	144

Clearly, that the allocation of lecturers to classes is not random, it does not mean that this is a problem for us. The tables above suggest that lecturers tend to choose their classes on the basis of schedules, rather than class size. This is probably because lecturers do not have to mark coursework, but only the final exam. Consequently, they might allocate more weight to the schedule of the course that they teach than to the number of students in a class. This is favourable to our strategy because schedule is probably not systematically related to academic performance, while the lecturer category could potentially have an effect on academic achievement. In the tables below, we include dummies for teacher category, day of the week that the course is taught, and whether the course is taught early in the morning of after 1:00 pm. Our results are qualitatively similar to the previous ones.

Table 14, Extended specification (instrumental variables)

	Business			
	Pass1	Pass2	Grade1	Grade2
$\frac{CS}{100}$	0.18	0.14	0.94	0.68
	(0.17)	(0.13)	(0.012)	(0.87)
Female	0.016	0.024	-0.056	-0.049
	(0.016)	(0.02)	(0.086)	(0.08)
Grade to enter	0.21	0.16	1.27	1.05
university	(0.001)	(0.009)	(0.057)	(0.044)
N indiv.	11288	11330	11329	11401
N. clusters	16	16	16	16

Include course, year, lecturer category, and schedule dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

Table 15: Extended specification (instrumental variables)

	Business & Law			
	Pass1	Pass2	Grade1	Grade2
$\frac{CS}{100}$	-0.345	-0.138	-2.935	-2.278
	(1.173)	(0.698)	(6.067)	(2.226)
Female	-0.017	-0.000	-0.140	-0.060
	(0.019)	(0.010)	(0.091)	(0.059)
Grade to enter	0.198	0.136	1.303	1.040
university	(0.014)	(0.015)	(0.079)	(0.050)
N indiv.	6174	6195	6178	6205
N. clusters	10	10	10	10

Include course, year, lecturer category, and schedule dummies

Standard errors, computed through bootstrap, are clustered at the year-group level

6 Conclusions

We have estimated the effect of class size on freshers' academic achievement during their first year of their degree (Business and Business&Law). We have used data from Univesidad Carlos III de Madrid because the way that freshers are allocated to groups in this university. Among freshers, groups are of different sizes being the only difference among them the first letter of their surname. We believe that this generates an exogenous source of variation that is uncorrelated to student's ability. In fact, we check that the number of freshers in a group is unrelated to previous academic achievement, what supports the idea that we can use the number of freshers in a group as a instrument for class size. We do not find a statistically significant impact of class size in academic performance.

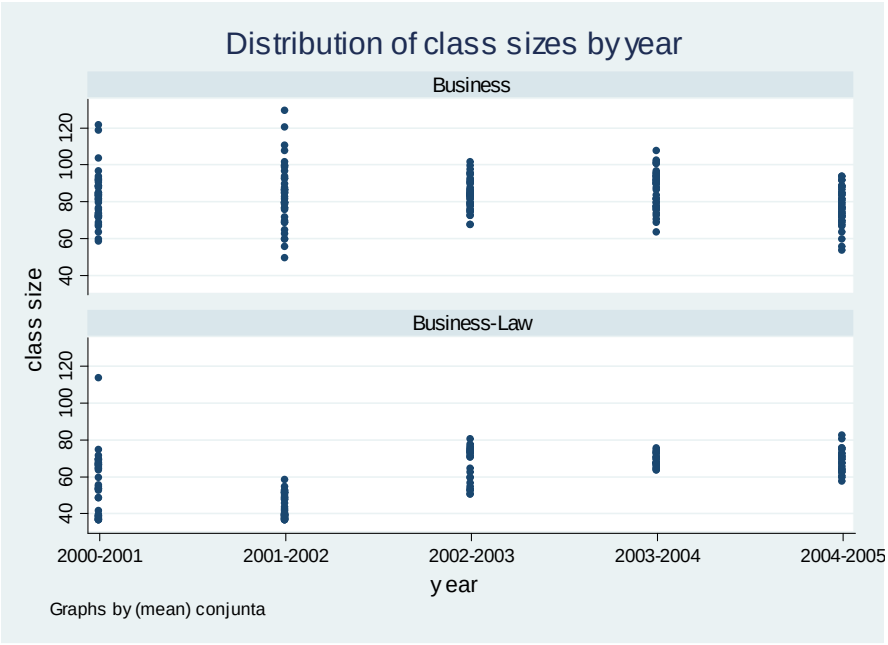

Figure 1: Distribution of class size per year

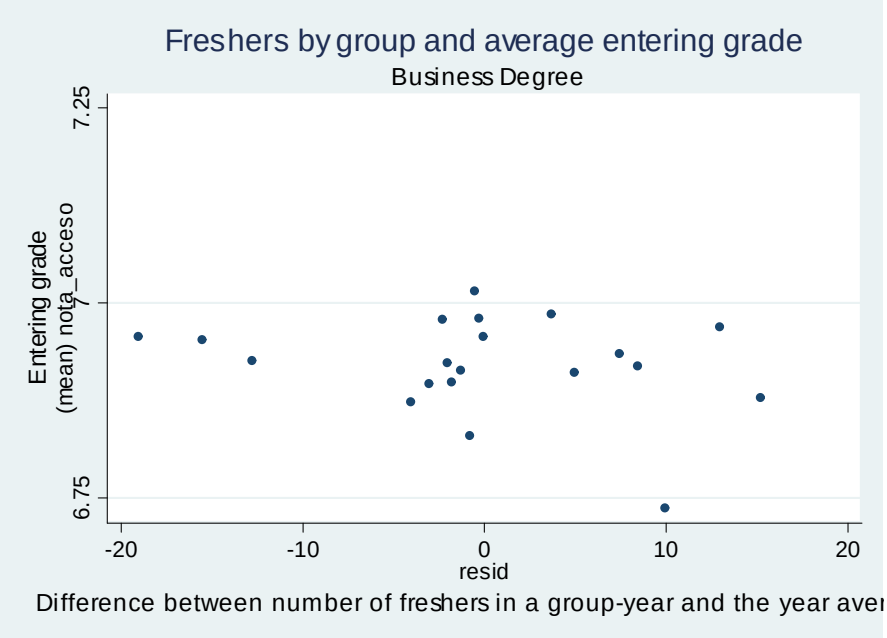

Figure 2: Scatterplot of the average grade to enter university in the group and the number of freshmen students in the group (difference with the year average)

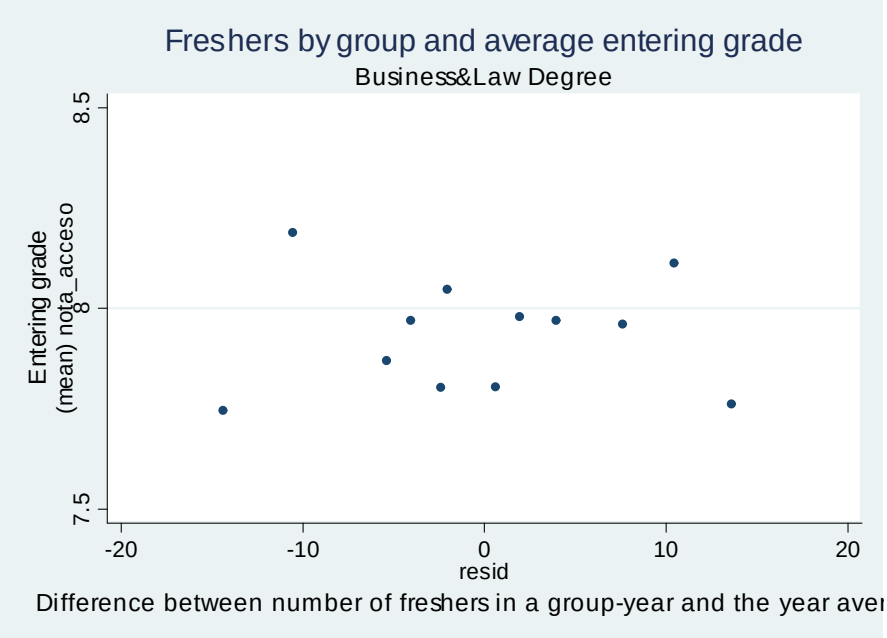

Figure 3: Scatterplot of the average grade to enter university in the group and the number of freshmen students in the group (difference with the year average)

7 Figures

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