UNIVERSIDAD CARLOS III DE MADRID

working papers

Working Paper 09-61
Economic Series (38)
October 2008

Departamento de Economía
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34) 916249875

Class Attendance and Academic Performance among Spanish Economics Students

Vincenzo Andrietti, Rosaria D'Addazio and Carlos Velasco Gómez

October 1, 2008

Abstract

This paper presents new evidence on the effects of class attendance on academic performance. We analyse survey data collected for an Introductory Econometrics Course at the Facultad de Ciencias Sociales y Jurídicas of Universidad Carlos III de Madrid, matched to administrative data. Using OLS-proxy regressions to control for unobservable student characteristics potentially correlated with attendance, we find a positive and significant effect of attendance on academic performance. However, the fact that instrumental variable regressions may be failing to account for the correlation not captured by the controls calls for further investigation based on panel data.

JEL classification: A22, I21.

1 Introduction

Evaluation of learning is a widely debated topic in the economic education literature. However, despite the common assumption that undergraduate students benefit from attending lectures, until the 1990s there was little evidence about attendance and its effects on students' learning. In line with Romer (1993) seminal article, a number of recent studies has found positive effects of attendance on performance, leading some authors to call for policies to increase or even mandate attendance.

The extent to which we can rely on these results is however not always clear, due to the fact that most studies leave unresolved the two main problems usually affecting the attendance rate variable. First, *self-reported attendance rates* are likely to be measured with error, inducing *attenuation bias* in the estimated coefficients. Second, attendance rate is potentially endogenous, given that students choice of whether to attend lectures is positively affected by unobservable individual characteristics, such as ability, effort, and motivation, that are also likely to have a positive effect on performance. This correlation determines positive *omitted variable bias* in the estimates.

This paper represent an attempt to address these issues through the collection of a novel dataset that combines survey and administrative information. First, careful attendance monitoring at each class meeting throughout the semester allows accurate measurement of attendance rate. Second, data collected include proxy variables of students ability, motivation and effort, as well as instrumental variables thought to be correlated with the potentially endogenous variables but uncorrelated with the error.

We also contribute to fill the lack of evidence for European Union countries, presenting novel empirical evidence for Spain.

The data for this study have been collected on students enrolled in the Introduction to Econometrics course at the "Facultad de Ciencias Sociales y Jurídicas" of "Universidad Carlos III de Madrid" in the spring semester of the academic year 2006-2007.

We exploit the richness of the data to define a set of regressors proxies of ability (registered and completed credit), effort (number of study hours, efforts to get lecture notes) and motivation (students' self reported interest in the course). By including them in our regression we attempt to disentangle the impact of attendance on performance from unobservable factors. The proxy-regression results show a positive effect of attendance on academic performance.

However, if proxies regressors were not perfect measures of unobservables, OLS-proxies regression would still be biased and inconsistent, incorrectly attributing to attendance the effect of the components of ability, effort and motivation not captured by the controls. One possible solution would be to find appropriate instruments for the potentially endogenous variable.

We look further into this issue using *distance from campus* and *having a job* as instruments for attendance. Although our instruments seem to be uncorrelated with the unobservables, their weak correlation with attendance leads to undesirable consequences, such as high standard errors and bias.

Failure of cross-sectional instruments variation to account for potential endogeneity of attendance calls for further investigation aiming at exploiting the variability of attendance and performance in the time dimensions, which would require collection of panel data.

The remainder of this work is organized as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 describes the empirical strategy. Section 5 presents the results. Section 6 concludes.

2 Literature

In his widely cited paper "Do students go to class? Should they?", Romer (1993) was one of the first authors to explore the relationship between student attendance and exam performance. From a preliminary survey on the extent of absenteeism at US colleges, he found that, on average, about one third of the students attending undergraduate economics courses at a representative sample of American universities were missing class on a "typical" day. In light of this result, Romer used attendance records at six meetings of his large size Intermediate Macroeconomics course in order to provide quantitative evidence on the effect of attendance on exam performance. The OLS estimates implied that, after controlling for unobservable aptitude, motivation and effort, attendance had a positive and significant impact on learning. On the basis of these findings, Romer recommended experimenting with mandatory attendance policies to enhance student performance[1].

Two earlier studies had also found an inverse relationship between absenteeism and exam performance[2]. In a paper examining student allocation time ($n = 216$), Schmidt (1983) reported that hours spent attending lectures and discussion sections positively affected course grades, even after controlling for hours of study. Park and Kerr (1990) used a multinomial logit model in order to identify the determinants of academic performance in a Money and Banking course ($n = 97$). After holding student motivation constant, they found that higher attendance was associated with better performance, although students' GPA and college entrance exam scores showed themselves to be even more important factors.

Following Romer's (1993) seminal paper, in the last fifteen years several studies have attempted to measure the impact of attendance on learning. Durden and Ellis (1995) uses students' self-reported number of absences in order to explore the relationship between absenteeism and academic achievement in several sections ($n = 346$) of a Principles of Economics course. Controlling for student differences in background, ability and motivation, they find a nonlinear effect of attendance on learning: while a few absences do not lead to worse grades, excessive absenteeism does.

Using data on a sample of about 400 Agricultural Economics students at four large US universities, Devadoss and Foltz (1996) find that, after taking into account motivational and aptitude differences across students, the difference in exam performance between a student with perfect attendance and a student attending only half of the classes is, on average, a full letter grade.

---

[1]Conflicting opinions on this controversial conclusion are expressed in Brauer et al. (1994).

[2]See McConnell and Lamphear (1969), Paden and Moyer (1969), Buckles and McMahon (1971), Browne et al. (1991) for previous evidence showing, on the contrary, no significant difference in exam performance between students who attended and students who skipped class.

Chan et al. (1997) examines the relationship between class attendance and academic performance in two small sections ($n = 71$) of a Principles of Finance course. After correcting for the selectivity bias due to student withdrawals by using Tobit and Heckman's two-stage models, they find a positive effect of attendance on performance. They also find that a mandatory attendance policy would not significantly enhance course grades.

Marburger (2001) applies an original approach to identify the "pure" effect of absenteeism on exam performance in a small size ($n = 60$) Principles of Microeconomics course. Student's absences records over the semester are matched with records of the class meetings when the material corresponding to each question of three multiple-choice exams was covered. Results from a probit regression show that missing class on a specific day significantly increase the likelihood to respond incorrectly to a multiple-choice question based on the material covered that day compared to students who were present. This finding suggests a negative relationship between absenteeism and academic performance.

Rodgers (2001) finds a small but statistically significant impact of attendance on academic performance in a sample of ($n = 167$) students enrolled in her Introductory Statistics course.

Using a sample of ($n = 371$) first-year italian Economics students, Bratti and Staffolani (2002) find that, after controlling for the number of study hours, the positive and significant effect of class attendance on performance is not robust to the inclusion of self study. Kirby and McElroy (2003) also base their analysis on a sample ($n = 368$) of first year economics students in Ireland. They find that class attendance is significantly affected by hours worked and travel time to university. On the other hand, tutorial attendance appears to enhance exam performance more than class attendance.

More recently, Stanca (2006) has been the author of the most comprehensive study to date. He uses a large panel data set collected from an Introductory Microeconomics course ($n = 766$) in a Italian university. The data combine administrative and survey sources. However, a limit of the data is that attendance to classes and tutorials is self reported by students. Applying three different econometric approaches (OLS-proxy regression, instrumental variables and panel estimators) to address the endogeneity of attendance rate variable, he bases his conclusions on panel data estimates indicating that attendance has an important independent effect on learning.

Although most studies find positive effects of attendance on performance, the extent to which we can rely on the evidence presented in the cited studies is not always clear. Most of the studies leave unresolved the two main problems usually affecting the attendance rate variable.

First, *self-reported attendance rates* are likely to be measured with error, inducing *attenuation bias* in the estimated coefficients. [3]

Second, attendance rate is potentially endogenous, given that students choice of whether to attend lectures is positively affected by unobservable individual characteristics, such as ability, effort, and motivation, that are also likely to have a positive effect on performance. This correlation determines positive *omitted variable bias* in the estimates. Existing studies based on cross-sectional data either do not face the endogeneity problem or attempt to disentangle the impact of attendance on performance from unobservable factors introducing proxy variables for unobservable ability (scores on college entry exams, grade point average), effort (number of study hours, completion of homework assignments) and motivation (students' self reported interest in the course). Stanca(2006) is the first to apply instrumental variables methods in this literature.

A few studies based on panel data exploit the variability of attendance and performance in the time dimension[4]. This allows to take into account time-invariant unobservable factors that affect both attendance and performance, and therefore to eliminate the omitted variable bias that characterizes estimates of the effect of attendance on performance even adequate instruments are not available.

Moreover, most of the literature focuses on the US. Kirby and McElroy(2003) for Ireland and Bratti and Staffolani(2002) and Stanca(2006) for Italy provide the only evidence available in the European Union context. This study contributes towards filling this gap, presenting novel evidence for

[3]Of the cited studies only Marburger (2001) records attendance at each class meeting.
[4]See Marburger (2001), Rodgers(2001) and Stanca(2006).

Spain.

3 Data

Our data were collected on a sample of undergraduate economics students at Universidad Carlos III de Madrid (UC3M) in the Spring semester of the academic year 2006-2007. The course was structured into six parallel sections[5] having both the same content (syllabus and textbook) and final examination. There were two 2-hours lectures per week over 13 weeks and four 2-hours tutorial meetings held approximately every three weeks in a computer laboratory[6]. Students were also encouraged to submit weekly problem sets in order to potentially increase the final grade. Attendance was recorded at the beginning of each[7] class meeting (both lectures and tutorials) by circulating a sign-in sheet. Students were previously informed that any absences would have not affected the course grade. Academic performance was measured by students' mark awarded in the final examination[8], which consisted of a 2-hours written test including three problems.

In addition to the three main variables of interest (test score, lecture attendance rate and tutorial attendance rate), observations on a number of control factors were also gathered by asking students to fill in two distinct

[5]All students were enrolled in a BA degree (*Licentiatura*) of the Facultad de Ciencias Sociales y Jurídicas. In particular, three cohorts included students from the BA degree in Economics and the remaining ones those from the BA degree in Economics-Law, the BA degree in Economics-Journalism and the bilingual group of the BA degree in Economics, respectively. The subject is compulsory for all students in their second-year of study.

[6]Computer sessions were devoted to get used to the statistical package Gretl in order to solve empirical problems with the help of a tutor.

[7]*Attendance monitoring* throughout the semester allowed us to avoid the *measurement error*, leading to biased estimates, which affects the alternative solutions generally used in the literature: *estimated* attendance rates, as reported by the students themselves (see e.g. Durden and Ellis, 1995, Stanca, 2006), and attendance records taken during a "sample period" of the semester, to be considered representative of average attendance (Romer, 1993).

[8]At UC3M there are two examination sessions (*convocatorias*) in every academic year: one ordinary at the end of the quarter (February for the courses taught in the Fall term and June for those held in the Spring term) and one extraordinary in September. In order to take any exam, students must previously enroll in the relevant subject after which they have only four attempts to pass each exam.

questionnaires. The former, consisting of 29 multiple-choice questions about family background and individual characteristics and habits, was administered during the first[9] class meeting. The latter, including a further 4 questions pertaining to students' study habits and teaching and subject evaluation, was compiled before starting the exam. These data were supplemented with the administrative records of UC3M providing detailed information on students' academic career[10]. Matching data from two different sources (survey and administrative) helps considerably in improving data quality. It is worth noting that such a strategy is a peculiarity of our study in comparison with the body of the literature[11]. The sample so obtained include 488 students, of whom 172 returninge incomplete questionnaires were dropped from the analysis. The actual sample is therefore composed by 316 individuals.

Descriptive statistics for the main variables used in the empirical analysis are presented in Table 1[12]. For ease of interpretation, exam score[13] was expressed as a percentage. In our sample, the average grade ranged between 0 and 100 around a mean value of 62.29. A typical student attended, on average, 42.99 per cent of lectures[14] and a lower percentage of tutorials (37.68). The set of control factors includes demographic variables (*male, siblings, live with family, distance*), information about individual and family background (*technology, father graduate, mother graduate, father not*

[9]Absent and non-attending students compiled it when taking the examination. Unlike most previous ones, our study includes in the empirical analysis even students who withdrew from the course and those who never attended class in order to avoid potential sample selection bias.

[10]See Table 1 in the appendix for a list of the main variables formally obtained as administrative data.

[11]Park and Kerr (1990), Chan et al. (1997) and Kirby and McElroy (2003) are the only studies base on matched data.

[12]We added a column specifying the source of the variables: survey or administrative database.

[13]Spanish university system employs a numerical grading scale, even though course grades are delivered to the students into a categorical form. In particular, marks, ranging from 0 to 10, are grouped into the following five categories: *Suspenso* (grades between 0 and 5), *Aprobado* (between 5 and 7), *Notable* (between 7 and 9), *Sobresaliente* (between 9 and 10) and *Matrícula de Honor* (10 or very close to this grade).

[14]This figure is substantially lower than those reported in the literature: Romer (67%), Stanca (67.4%), Rodgers (64%, 70%), Marburger (82%), Devadoss and Foltz (89%). It is comparable only with that observed by Kirby and McElroy (47%).

working, mother not working), students' characteristics (*pc*) and proxies for individual unobservable factors. In particular, ability was measured by two indicators: *credits enrolled*, ranging between 35 and 135 around a mean value of 86.72 and *credits completed*, showing an average value of 149.21, with a range from 48 to 313. Effort was proxied by four variables: weekly *hours of study*, registering a mean value of 3.13, with a range between 0 and 20; *never asking notes*, *sometimes asking notes* and *often asking notes*, dummy variables measuring how intensely the students searched for lectures notes. All three averaged quite low (0.06, 0.32 and 0.19, respectively). Measures of motivation included *subject evaluation* and *teaching evaluation*, as reported by the students themselves on a 0-100 scale. They registered average values of 62.61 and 65.93, respectively.

Table 2 provides summary statistics comparing non-attending students versus attending ones. Interestingly, students with a positive attendance rate scored significantly better than students who never attended lectures: the difference in exam performance between the two groups was approximately 11 percentage points (63.07 and 51.82, respectively). Moreover, by considering only those students who attended at least one lecture, we discovered a similar average attendance rate (46.20 compared to 42.99 for the overall sample).

Table 3 shows descriptive statistics (means) for some indicators of performance, attendance, ability and effort by students' degree course. In the last row of the table the overall means are displayed. On average, students enrolled in the Economics-Law degree revealed themselves to be the best ones, as they obtained the best marks (average grade of 71.81, almost 10 percentage points above the overall mean of 62.29), attended the highest percentage of lectures (50.41 compared to the overall mean rate of 42.99) and completed the highest number of credits (194.01 against the overall mean value of 149.21). On the contrary, students performing worst were those enrolled in the Economics-Journalism degree: on average, they scored 56.93 and registered 120.63 credits completed. The lowest attendance rate belonged, instead, to the students from Economics-Bilingual degree: average values of 24.48 per cent for lectures and 23.46 per cent for tutorials. Students from Economics degree reported values generally close to the overall means.

Finally, the average values of weekly study hours and credits enrolled were found in line with the overall means (3.13 and 86.72, respectively) for all the degree courses.

4 Empirical Strategy

Our goal is to specify and estimate an appropriate education production function (EPF) explaining academic performance in terms of class attendance rate, all other things being equal. According to the EPF approach[15], a basic learning model can take the following form:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 \mathbf{x}_{i2} + u_i \qquad i = 1, 2, \ldots, n \tag{1}$$

where y_i is the educational outcome for individual i, measured by exam score, x_{i1} is class attendance rate, $\mathbf{x}_{i2}$ is a vector including selected inputs into the achievement process and u_i is an error term containing all the other factors influencing academic performance.

Input measures are those suggested by both theoretical considerations and the results of previous studies. They range from school inputs to family background, from socio-economic variables to students' study habits. Among the several factors which matter for academic achievement there are also certain unobservable student characteristics, such as ability, effort and motivation. Since these same variables are potentially correlated with the students' propensity to attend class, excluding them from the model would give rise to a problem of omitted variable bias. In this study, we survey two different econometric approaches accounting for possible sources of endogeneity in order to estimate a causal relationship between attendance and exam performance.

One way to compensate for missing data on specific input variables is to include in the OLS regression one or more *proxy variables*. Consider a population model with two explanatory variables, one of which (x^*_{i2}) is unobserved:

[15] See, among others, Lazear (2001), Coates (2003) and Todd and Wolpin (2003).

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x^*_{i2} + u_i \quad (2)$$

and suppose we have a proxy variable (x_{i2}) for x^*_{i2}. On the basis of the relationship between the unobservable factor and the proxy variable, captured by the simple regression model:

$$x^*_{i2} = \delta_0 + \delta_2 x_{i2} + \eta_i \quad (3)$$

we can regress y_i on x_{i1} and x_{i2}. Such a procedure can lead to a consistent estimator of the slope parameter β_1 under the following assumptions about u_i and η_i:

1. the error u_i is uncorrelated with x_{i2}. This condition is equivalent to assuming that x_{i2} is *irrelevant* in the population model once x_{i1} and x^*_{i2} have been controlled for. In terms of conditional expectations, we can write:
$$E(y_i|x_{i1}, x^*_{i2}, x_{i2}) = E(y_i|x_{i1}, x^*_{i2}) \quad (4)$$

2. the error η_i is *uncorrelated* with x_{i1} and x_{i2}. Assuming this requires x_{i2} to be a "good" proxy for x^*_{i2}. In a conditional mean sense, we have:
$$E(x^*_{i2}|x_{i1}, x_{i2}) = E(x^*_{i2}|x_{i2}) = \delta_0 + \delta_2 x_{i2} \quad (5)$$
that is x^*_{i2} has zero correlation with x_{i1} once x_{i2} has been controlled for.

In our analysis ability is proxied by *credits enrolled* and *credits completed*, effort by *hours of study*, *never asking notes*, *sometimes asking notes* and *often asking notes*, motivation by *subject evaluation* and *teaching evaluation*.

Proxy variables may be difficult to find in practice and the ones available do not always satisfy the properties needed to produce a consistent estimator of β_1. In such cases an alternative approach to the endogeneity problem is offered by the method of *instrumental variables (IV)*. It allows to consistently estimate the unknown parameters of the population regression function when the regressor of interest (x_{i1}) is correlated with the error term u_i, for instance in the presence of omitted variables.

Instrumental variables estimator:

$$\hat{\beta}_1^{IV} = \frac{Cov(z_i, y_i)}{Cov(z_i, x_i)} \tag{6}$$

eliminates such a correlation provided the "instruments" z_i satisfy the two conditions for instrument *validity*:

1. *Instrument Relevance*: z_i is correlated with x_{i1}

$$Cov(z_i, x_{i1}) \neq 0 \tag{7}$$

   This assumption can be verified by regressing x_{i1} against z_i and the included exogenous variables. Instruments not satisfying such a condition are called "weak". *Weak instruments*[16] imply a 2SLS estimator biased and 2SLS t-statistics and confidence intervals unreliable.

2. *Instrument Exogeneity*: z_i is uncorrelated with u_i

$$Cov(z_i, u_i) = 0 \tag{8}$$

   This condition can be partially checked with the *test of overidentifying restrictions* as long as the number of instruments exceeds the number of included endogenous variables. If the instruments are not exogenous, then the 2SLS estimator is inconsistent.

In the following we run *two stage least squares* regression using *distance* covered to reach campus (in kilometers) and *work* (1=working student) as instruments for attendance.

[16] We can check for instrument "weakness" by computing an F test. When there is a single endogenous regressor, we face with weak instruments if the first-stage F-statistics is less than 10 (Bound, Jaeger and Baker (1995)).

5 Results

We start by estimating alternative specifications of our learning model by OLS regression. Table 4 presents the point estimates for the overall sample ($n = 316$). Attendance is found to have a small but statistically significant (at the one percent level) effect on performance in all models. On average, attending an extra percentage point of lectures increases test score of about 0.13 percentage points. It should be noted that the estimated coefficient on attendance keeps basically the same after controlling for both individual characteristics and unobservable factors, as shown in columns 2 to 5. One possible explanation for such a result is that we could have not selected good proxies for ability, effort and motivation.

Among the control variables included in the OLS models, only a few have a significant effect on student performance. In specifications 2 and 4 live with family is negatively and significantly associated to performance (at the five and ten percent levels, respectively). As reported in columns 3 and 5, credits completed appears as one of the most important determinants of academic performance. In both models the coefficient on this ability indicator is statistically significant at the one percent level and has the expected sign: one additional credit completed corresponds to a 0.07 percent higher test score. The point estimate for subject evaluation is also quantitatively small (0.09 and 0.10 in specifications 4 and 5, respectively) and significant at the five percent level. Finally, in contrast with the majority of the literature, we find no significant difference in the performance of males and females.

Table 5 shows the results obtained by restricting the sample to the 294 students who attended at least one lecture. Interestingly, we find that attendance rate is not sensitive to the exclusion from the data set of those students who never attended class. In fact, the point estimates keep almost unchanged. For instance, the coefficient on attendance falls from 0.12 to 0.10 in the basic univariate specification and from 0.13 to 0.11 in the remaining models. Subject evaluation has a coefficient only slightly higher (from 0.09 to 0.11 in model 4 and from 0.10 to 0.13 in specification 5), whereas credits completed is exactly the same both in magnitude and statistical significance.

Only credits enrolled now becomes significant, at the five percent level.

We finally compare the effects of lecture and tutorial attendance on student performance. The results are reported in Table 6. We run three different OLS regressions including the complete set of controls. The first specification (5) contains lecture attendance as the main regressor; in the second one (5a) lecture attendance is replaced with tutorial attendance, whereas in the last one (5b) lectures and tutorials are jointly included. The coefficient on tutorial in column 2 indicates that the effect tutorial attendance on academic performance is very close to that of lecture attendance: 0.09 and 0.13 percent improvement in final grade for one additional percentage point of attendance, respectively. Adding both variables in the same specification does not change the relationship between the estimated coefficients. As shown in column 3, the point estimates are quite similar (0.11 and 0.02 for lecture and class attendance, respectively). This result suggests that the respective roles of lectures and classes cannot be identified separately.

As an alternative approach to the endogeneity problem, we then run *two stage least squares* regression using *distance* covered to reach campus (in kilometers) and *work* (1=working student) as instruments for attendance. The results shown in Table 7 are qualitatively similar to the previous ones. The main finding is that now the estimated effect of attendance on performance is substantially higher (nearly 0.50, that is about four times higher than the point estimates obtained with models that do not take into account endogeneity or that simply employ proxy variables) and slightly significant. Also, we would have expected a reduction on the estimated coefficient, given that the OLS-proxies results may be still upward biased. The rise in estimated coefficient and in standard errors may be due to the fact that our instruments are only weakly correlated with attendance. This result suggests that instrumental variables methods are not failing in taking into account the remaining endogeneity of the attendance rate variable.

6 Conclusions

Although continuous evaluation of students learning is among the principles inspiring the European Space of Higher Education (Bologna Process), evidence about the effect of class attendance on academic performance is lacking for most European Union countries. This is partly due to the lack of adequate data and partly due to methodological problems. This analysis represents a first step towards filling this gap. Using new data that combines different sources of information and regression proxies techniques we find a significant effect of lecture attendance on academic performance. However, failure of cross-sectional instruments variation to account for potential endogeneity of attendance calls for further investigation aiming at exploiting the variability of attendance and performance in the time dimensions, which would require collection of panel data.

References

[1] Bound, J., Jaeger, D.A. and Baker, R.M. (1995). "Problems with Instrumental Variables Estimation When the Correlation Between the Instrument and the Endogenous Explanatory Variable Is Weak.", *Journal of the American Statistical Association*, 90 (430), 443-450.

[2] Bratti, M. and Staffolani, S. (2002). "Student time allocation and educational production functions", *Quaderni di ricerca, Dipartimento di Economia - Universita' di Ancona*, July, no. 170.

[3] Browne, N.M., Hoag, J., Wheeler, M.V. and Boudreau, N. (1991). "The Impact of Teachers in Economic Classrooms", *Journal of Economics*, 17, 25-30.

[4] Buckles, S.G. and McMahon, M.E. (1971). "Further Evidence on the Value of Lecture in Elementary Economics", *Journal of Economic Education*, 2(2), 138-141.

[5] Chan, K.C., Shum, C. and Wright, D.J. (1997). "Class attendance and

student performance in principles of finance", *Financial Practice and Education*, Fall/Winter, 7(2), 58-65.

[6] Coates, D. (2003). "Education production functions using instructional time as an input", *Education Economics*, 11(3), 273-292.

[7] Devadoss, S. and Foltz, J. (1996). "Evaluation of factors influencing student class attendance and performance", *American Journal of Agricultural Economics*, August, 78(3), 499-507.

[8] Dolado, J.J. and Morales, E. (2008). "Which Factors Determine Academic Performance of Undergraduate Students In Economics? Some Spanish Evidence", Working Paper.

[9] Durden, G.C. and Ellis, L.V. (1995). "The effects of attendance on student learning in principles of economics", *American Economic Review Papers and Proceedings*, May, 85(2), 343-346.

[10] Kirby, A. and McElroy, B. (2003). "The effect of attendance on grade for first-year Economics students in University College Cork", *The Economic and Social Review*, 34(3), 311-326.

[11] Lazear, E.P. (2001). "Educational production", *Quarterly Journal of Economics*, 116(3), 777-803.

[12] Marburger, D.R. (2001). "Absenteeism and undergraduate exam performance", *Journal of Economic Education*, Spring, 32(2), 99-109.

[13] McConnell, C.R. and Lamphear, C. (1969). "Teaching Principles of Economics Without Lectures", *Journal of Economic Education*, 1(4), 20-32.

[14] Paden, D.W. and Moyer, M.E. (1969). "The effectiveness of Teaching Methods: The Relative Effectiveness of Three Methods of Teaching Priciples of Economics", *Journal of Economic Education*, 1, 33-45.

[15] Park, K.H. and Kerr, P.M. (1990). "Determinants of academic performance: a multinomial logit approach", *Journal of Economic Education*, Spring, 21(2), 101-111.

[16] Rodgers, J.R. (2001). “A panel-data study of the effect of student attendance on university performance”, *Australian Journal of Education*, 45(3), 284-295.

[17] Romer, D. (1993). “Do students go to class? Should they?”, *Journal of Economic Perspectives*, Summer, 7(3), 167-174.

[18] Schmidt, R.M. (1983). “Who maximizes what? A study in student time allocation”, *The American Economic Review*, May, 73(2), 23-28.

[19] Stanca, L. (2006). “The Effects of Attendance on Academic Performance: Panel Data Evidence for Introductory Microeconomics”, *Journal of Economic Education*, 37(3), 251-266.

[20] Stock, J.H. and Watson M.W. (2003). “Introduction to Econometrics”, *Addison Wesley.*

[21] Todd, P.E. and Wolpin, K.I. (2003). “On the specification and estimation of the production function for cognitive achievement”, *The Economic Journal*, February, 113, F3-F33.

[22] Wooldridge, J.M. (2006). “Introductory Econometrics. A Modern Approach”, *South-Western.*

Table 1: Descriptive Statistics

Variable	Source	Mean	Std. Dev.	Min	Max
Score (%)	admin	62.29	17.40	0.00	100.00
Attendance (%)	survey	42.99	30.58	0.00	100.00
Tutorial (%)	survey	37.68	32.45	0.00	100.00
Male	admin	0.55	0.50	0.00	1.00
Siblings	survey	1.25	0.91	0.00	5.00
Live with family	survey	0.73	0.44	0.00	1.00
Distance	survey	18.04	14.54	0.00	80.00
Technology	admin	0.21	0.41	0.00	1.00
Father graduate	survey	0.35	0.48	0.00	1.00
Mother graduate	survey	0.27	0.44	0.00	1.00
Father not working	survey	0.08	0.27	0.00	1.00
Mother not working	survey	0.35	0.48	0.00	1.00
Pc	survey	0.96	0.21	0.00	1.00
Credits enrolled	admin	86.72	13.78	35.00	135.00
Credits completed	admin	149.21	56.17	48.00	313.00
Hours of study	survey	3.13	2.49	0.00	20.00
Never asking notes	survey	0.06	0.24	0.00	1.00
Sometimes asking notes	survey	0.32	0.47	0.00	1.00
Often asking notes	survey	0.19	0.39	0.00	1.00
Subject evaluation	survey	62.61	24.40	0.00	100.00
Teaching evaluation	survey	65.93	22.70	0.00	100.00

Note: n=316.

Table 2: Descriptive Statistics by attendance rate

Variable	Attendance=0 (n=22)		Attendance>0 (n=294)	
	Mean	Std. Dev.	Mean	Std. Dev.
Score (%)	51.82	17.41	63.07	17.17
Attendance (%)	0.00	0.00	46.20	29.27
Tutorial (%)	1.14	5.33	40.42	31.97
Male	0.55	0.51	0.55	0.50
Siblings	1.05	0.65	1.27	0.93
Live with family	0.73	0.46	0.73	0.45
Distance	22.40	19.52	17.72	14.10
Technology	0.14	0.35	0.22	0.41
Father graduate	0.23	0.43	0.36	0.48
Mother graduate	0.18	0.39	0.28	0.45
Father not working	0.09	0.29	0.08	0.27
Mother not working	0.41	0.50	0.35	0.48
Pc	0.95	0.21	0.96	0.21
Credits enrolled	93.77	17.04	86.20	13.40
Credits completed	144.73	45.74	149.55	56.92
Hours of study	4.45	4.36	3.03	2.27
Never asking notes	0.05	0.21	0.06	0.25
Sometimes asking notes	0.50	0.51	0.31	0.46
Often asking notes	0.18	0.39	0.18	0.39
Subject evaluation	57.50	26.58	62.99	24.23
Teaching evaluation	55.91	23.69	66.68	22.49

Table 3: Descriptive Statistics (means) by degree course

Degree Course	Score (%)	Attendance (%)	Tutorial (%)	Credits Enrolled	Credits Completed	Hours of study
Economics	59.02	44.10	40.36	86.43	132.44	3.17
Economics-Bilingual	61.56	24.48	23.46	86.89	159.67	3.00
Economics-Journalism	56.93	35.84	32.32	86.70	120.63	3.06
Economics-Law	71.81	50.41	39.63	87.26	194.01	3.13
Total	62.29	42.99	37.69	86.72	149.21	3.13

Note: n=316.

Table 4: Determinants of academic performance: OLS estimates (full sample)

Independent Variable	OLS (1)		OLS (2)		OLS (3)		OLS (4)		OLS (5)	
Attendance	0.12	***	0.13	***	0.13	***	0.13	***	0.13	***
Male			0.82		0.27		0.59		−0.07	
Siblings			−0.76		−0.92		−0.77		−0.97	
Live with family			−4.20	**	−3.10		−3.50	*	−2.5	
Pc			−0.81		−0.21		−0.71		−0.52	
Technology			1.40		1.80		1.80		2.10	
Credits enrolled					0.11				0.11	
Credits completed					0.07	***			0.07	***
Hours of study							0.30		0.14	
Never asking notes							5.30		3.50	
Sometimes asking notes							2.60		2.00	
Often asking notes							0.77		1.30	
Subject evaluation							0.09	**	0.10	**
Teacher evaluation							0.01		0.00	
Constant	57.00	***	56.00	***	36.00	***	47.00	***	28.00	***
R^2	0.04		0.15		0.22		0.18		0.24	

Note: n=316

Significance levels: (*) p< 0.10, (**) p< 0.05, (***) p< 0.01.

Other control factors (dummies): father graduate, mother graduate, father not working, mother not working.

Table 5: Determinants of academic performance: OLS estimates (attendance>0)

Independent Variable	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)
Attendance	0.10 ***	0.11 ***	0.11 ***	0.11 ***	0.11 ***
Male		1.60	1.00	1.40	0.62
Siblings		−1.10	−1.40	−1.20	−1.50
Live with family		−4.10 *	−2.90	−3.40	−2.10
Pc		−1.70	−1.30	−0.82	−0.91
Technology		0.52	0.96	0.88	1.20
Credits enrolled			0.16 **		0.17 **
Credits completed			0.07 ***		0.07 ***
Hours of study				0.46	0.23
Never asking notes				4.50	2.60
Sometimes asking notes				2.00	0.91
Often asking notes				1.50	2.00
Subject evaluation				0.11 **	0.13 ***
Teacher evaluation				0.02	0.01
Constant	59.00 ***	59.00 ***	34.00 ***	47.00 ***	24.00 ***

Note: n=294

Significance levels: (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$.

Other control factors (dummies): father graduate, mother graduate, father not working, mother not working.

Table 6: Determinants of academic performance: OLS estimates (lectures vs tutorials)

Equation	OLS (5)		OLS (5a)		OLS (5b)	
Attendance	0.13	***			0.11	**
Tutorial			0.09	***	0.02	
R^2	0.24		0.23		0.24	

Note: n=316

Significance levels: (*) p< 0.10, (**) p< 0.05, (***) p< 0.01.

Table 7: Determinants of academic performance: IV estimates

Variable	(1)		(2)		(3)	
	FS regres.	2SLS regres.	FS regres.	2SLS regres.	FS regres.	2SLS regres.
Attendance		0.48		0.50 **		0.50 **
Distance	−0.12				−0.08	
Working student			−9.13 ***		−8.84 ***	
F test	0.39		0.01		0.02	
Overid. restr. test						0.99
Hausman test		0.54		0.07 *		0.06 *

Note: n=316.

Significance levels: (*) p< 0.10, (**) p< 0.05, (***) p< 0.01.