Am I missing something?

The effects of absence from class on student performance

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Abstract.

We exploit a rich administrative panel data-set for cohorts of Economics students at a UK university in order to identify causal effects of class absence on student performance. We exploit the panel properties of the data to control for unobserved heterogeneity across students and hence for endogeneity between class absence and academic performance of students stemming from the likely influence of effort and ability on both absence and performance. Our estimations also exploit features of the data such as the random assignment of students to classes and information on the timetable of classes, which provides potential instruments in our identification strategy. Among other results we find, from a quantile regression specification, that there is a causal effect of absence on performance for students: missing class leads to poorer performance. There is evidence that this is particularly true for better-performing students, consistent with our hypothesis that effects of absence on performance are likely to vary with factors such as student ability.

1.   Introduction

The analysis of the factors associated with educational attainment and performance has been a major focus of work in the last decade or so as economists have attempted to obtain a deeper understanding of the processes associated with the acquisition of human capital. Work has focused on the importance of factors such as class size and peer effects, *inter alia*; see, for example, Hanushek *et al*, (2003), Hoxby, (2000), Krueger (2000), Ehrenberg *et al*. (2001), and Burtless (1996). Much of the work has concentrated on the educational attainment of pupils in compulsory schooling, with less attention on higher education. Yet the processes associated with post-compulsory human capital accumulation are internationally important given increasing participation rates and the economic significance of the higher education (HE) sector in modern economies. A further motivation for analysing HE processes specifically is that their nature is likely to be fundamentally different to those characterising earlier-stage cognitive development, with greater student autonomy in study one obvious reason for this. One aspect of this autonomy is the relative freedom of students in HE to choose to absent themselves from class. More generally, the modes of study of HE students are less prescribed than in compulsory education: the responsibility for the efficient allocation of study time lies largely with the student – though this is not necessarily uniformly true across all university courses. Our work focuses on issues regarding the relationship between absence from class and academic performance of university students, a subject which has attracted attention since the influential paper of Romer (1993). Our analysis concentrates on variations across students in the causal impact of absence on performance.

Currently, in the UK, there are significant changes taking place in HE. Following several decades in which the unit of resource has fallen, the introduction of tuition fees for home students offers the potential prospect of better resourced teaching. There are a number

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of possible implications for the ways in which the nature of the teaching and learning environment in universities might evolve. Traditionally, university teaching in the UK is based on large-group lectures and small-group classes. Attendance at lectures has been seen as optional. Class attendance, however, has been regarded as compulsory for various reasons, which include the perception that: (i) that the value added in class is greater than that in lectures and students might not appreciate this and (ii) class attendance by each student has positive externalities for other students through the contributions each can make to the learning process. With declining resources, class sizes have been increasing across the HE sector and this has undermined the strength of both of these arguments. Indeed, it is likely that in large classes attendance imposes negative externalities through congestion effects.[1] There is a view in the sector that small group teaching is no longer as effective as it was and that students, perceiving this, have higher abstention rates. There are various responses to this, including: abandoning small group teaching; resourcing it better; reforming it; making attendance compulsory; and/or creating more explicit incentives for attendance. Developing a better understanding of the effects of class attendance on student outcomes seems timely.

Our empirical analysis exploits a rich administrative panel dataset for cohorts of Economics students at a UK university. We exploit the panel properties of the data to control for unobserved heterogeneity across students and hence for endogeneity between attendance and performance stemming from the likely influence of ability, effort, and motivation on both. That students are randomly assigned to classes avoids the potential endogeneity problems that occur when students can self select into classes. Finally, we use the idea that the time slot of the class in the weekly timetable produces exogenous variation in a student's

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[1] Lazear (2001) develops a theoretical model in which classroom education has public good characteristics. In Lazear's model, a disruptive student reduces others' learning.

attendance and hence acts as an instrument in order to identify a causal effect of attendance on performance.

From our empirical analysis, we find, among other results, that there is a significant association between missing class and student performance, but that this effect is weakened – but remains significant – when controlling for unobserved individual effects. In a quantile regression specification, it emerges that the adverse effect of missing class is greater for better-performing students, consistent with the hypothesis that effects are likely to vary with factors such as student ability.

In the next section, we present a brief literature review. This is followed, in Section 3, by a theoretical motivation for the analysis of the relationship between absence and student performance. Section 4 presents the data, and key summary statistics, based on cohorts of economics students at the UK university, while, in Section 5 we describe the econometric modelling approach. Section 6 discusses the results from our econometric analysis of the causal effects of tutorial absence on student performance. Section 7 concludes and offers further remarks.

2.   Contextual literature

Romer (1993) presented quantitative evidence on absenteeism and performance in economics courses at 3 universities in the US. Romer reported absenteeism to be 'rampant', with an overall absence rate of about one-third. Romer also reported evidence consistent with the hypothesis that absence affects student performance adversely, while acknowledging that no causal effect had been demonstrated given the endogenous nature of the relationship between attendance and performance. The general assumption in the literature is that more able (and motivated and hard-working) students are both more likely to attend class and to score more highly in their modules. Thus, in the absence of adequate proxies for such personal

characteristics, part of any estimated effect of class attendance will reflect a form of (upward) ability bias arising out of endogenous selection. Romer does include in his regression analysis controls for prior grade point average on the grounds that these will capture some of the otherwise unobserved heterogeneity across students. Indeed, Romer notes that as the estimated effect of prior performance depends in part on previous class attendance, the inclusion of prior scores could cause a downward bias in the estimate of the effects of attendance on performance; part of the effect being captured in the control variable.

Following Romer (1993), Durden and Ellis (1995) analyse survey data on absences for 346 economics students on a principles of economics module at a single US university. They report that the average effect of absences on performance is modest, but that there are substantial adverse effects when absence exceeds certain threshold levels. Rodgers (2002), using data on attendance in an introductory statistics module at an Australian university, finds a strong positive association between attendance and performance but, comparing across cohorts, reports that the introduction of a scheme which raised attendance was not associated with enhanced performance. Rodgers infers that attendance alone does not improve achievement.

Stanca (2006) uses a survey-based panel data set of students taking a microeconomics module at an Italian university. The analysis exploits the panel nature of the data to take account of unobserved characteristics correlated with attendance and produces estimates indicating a significant positive causal effect of attendance on performance. Devadoss and Foltz (1996) also report significant positive effects of class attendance on student performance from a survey-based analysis of students, across 4 US universities, taking classes in agricultural economics. The analysis exploits survey responses to questions eliciting information on prior attainment, student effort and motivation. This information generates proxies for these typically unobserved characteristics. Finally, Martins and Walker

(2006) find no significant effects of class attendance on performance for students in the Economics Department at a leading UK University, and also find no significant effects of smaller classes on improved performance.

Our own analysis attempts to uncover causal effects of class attendance (or, more specifically, absence – its converse) on the performance of students taking core modules in the second (intermediate) year[2] of an economics degree course at a UK university. We exploit data for 3 cohorts of students and for 3 modules for each student. Given the panel nature of the data we are able to control for unobserved heterogeneity. We also control for previous attainment and use precise information on the students' class timetables to generate instruments which we employ in the strategy for the identification of causal effects.

3.   Theoretical discussion

Consider an educational production function[3] of the following form:

$$p = p(c,q,r) , \qquad\qquad (1)$$

where p is a measure of a student's educational performance, c is the amount of time allocated by the student to attending class, q is the amount of time spent in alternative forms of study activity, and r captures personal characteristics such as ability, effort and motivation.

Suppose that the objective function of the student is to maximise performance, given by equation (1). Among the constraints will be a time constraint of the form:

$$c + q \leq \bar{t} , \qquad\qquad (2)$$

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[2]   We describe the selection and properties of the data and of the institutional context in more detail in the Section 4.

[3]   For a discussion of the estimation of production functions for cognitive achievement, see Todd and Wolpin (2003).

where $\bar{t}$ is the maximum amount of time available for study in a given period. In the production function, assume initially that c and q are neither complements nor substitutes but are independent. The problem for the 'grade'-maximising student is to allocate their time efficiently between attending class and alternative study time uses, such as attending large-group lectures, private study, or completing assignments. Privately efficient time allocation – we are ignoring externality and public good characteristics of classroom attendance for now (see Lazear, 2001) – will require the student to have knowledge of the marginal productivity of c and q in (1).

In reality, marginal products are likely to be person-specific: one of the challenges for the student is to reflect on their own learning strategies and capacities in developing for themselves a mature appreciation of 'what works best for them' – that is, of their own marginal productivities for the factors in their educational production function. Implicitly, the importance of this is embodied in the current emphasis on 'reflective learning' and 'personal development planning' in UK HE. One of the reasons for not selecting first year students in our data analysis is the acknowledgement that only by the second year will students have had sufficient experience of HE to be able to make informed judgements about their optimal learning strategies. This is also recognised by most UK universities as, typically, first year performance does not contribute to final degree marks and classifications.

Assume for now that the student has accurate information regarding the parameters of their own educational production function. Assume also that marginal products of study time are positive but diminishing in each study activity and are independent of each other and of

ability, i.e. $\dfrac{\partial p}{\partial c} \equiv mpc > 0$, $\dfrac{\partial p}{\partial q} \equiv mpq > 0$, $\dfrac{\partial^2 p}{\partial c^2} < 0$, $\dfrac{\partial^2 p}{\partial q^2} < 0$, $\dfrac{\partial^2 p}{\partial c \partial q} = 0$, $\dfrac{\partial^2 p}{\partial c \partial r} = 0$, and

$\dfrac{\partial^2 p}{\partial q \partial r} = 0$. We additionally assume that, $\dfrac{\partial p}{\partial r} > 0$. Some of these assumptions will be relaxed

later. With these assumptions, we can represent diagrammatically the solution to the problem defined in equations (1) and (2) for the grade-maximising student: see Figure 1a.
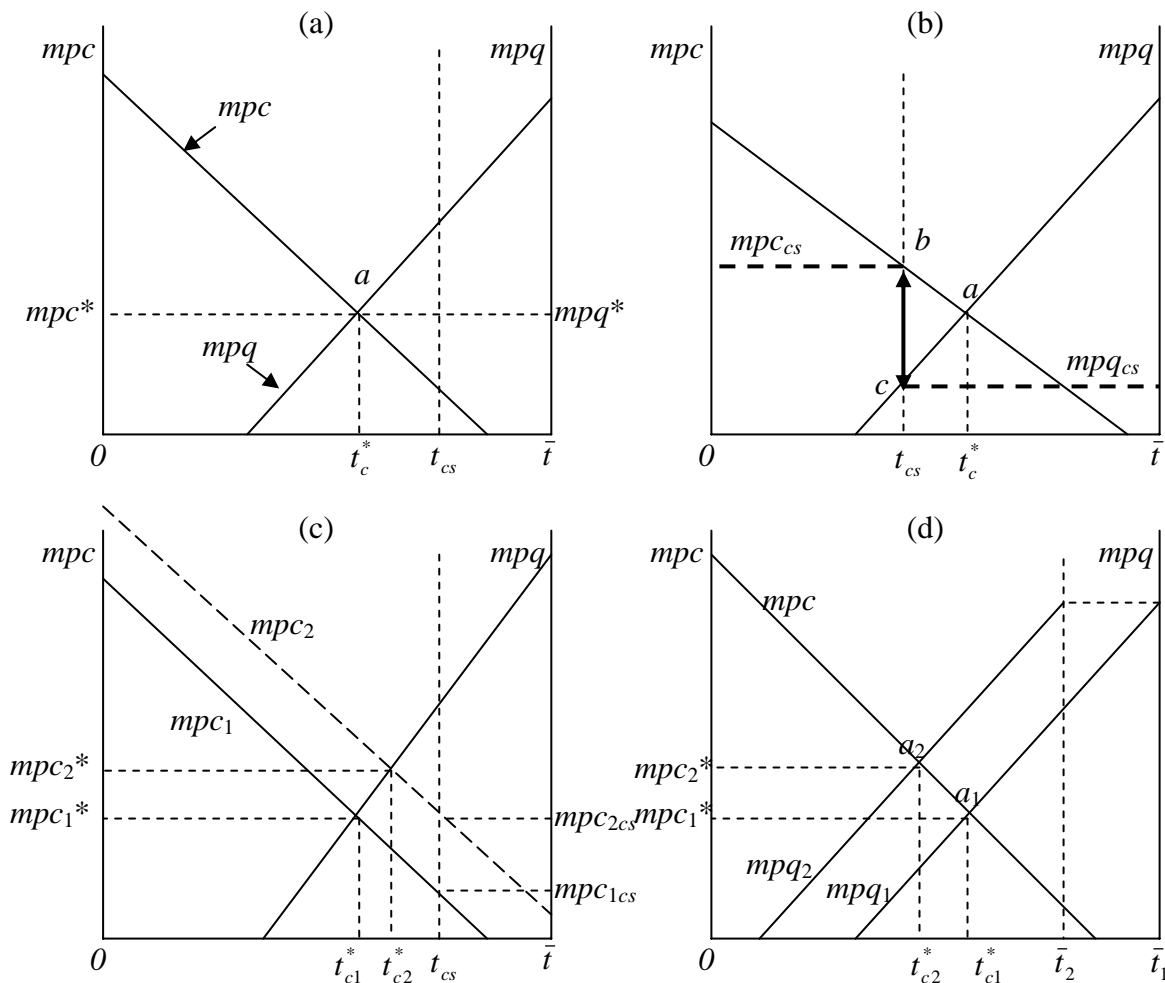

Figure 1 - Efficient study-time allocation.

From Figure 1a, we can see that the grade-maximising student will optimise at point a, choosing to attend t_c^* hours of class and engaging in $\bar{t} - t_c^*$ hours of additional study. Whether this involves absences from class will depend on the number of scheduled classes available to the student. If there are significant external net benefits of attending class, then – depending on institutional resources – the number of classes supplied to the student, denoted by t_{cs}, is more likely to exceed the student's optimal number, and hence $t_{cs} > t_c^*$, as in Figure 1a. If, on the other hand, $t_{cs} < t_c^*$, then the outcome will be inefficient, at least according to

the student's private calculus: as shown in Figure 1b, where there is now a wedge between the marginal products: $mpc > mpq$.

In the case described in Figure 1a, the optimising student will choose to miss $t_{cs} - t_c^*$ hours of class. At the margin, were the student required to attend all t_{cs} classes, then there would be a fall in the student's performance level as $mpq > mpc$ for the marginal classes. Suppose that class attendance is compulsory but that absence is not penalised. Then the propensity of students to miss at least some fraction of the sub-optimal $t_{cs} - t_c^*$ classes will depend on their attitudes to compliance. Suppose that this is randomly distributed across students. Then it follows that, under the assumptions of the model, in a learning environment in which class attendance is regarded as compulsory but in which, without enforcement, some individuals absent themselves nonetheless, class absences in the range $t_{cs} - t_c^*$ will be associated with improved performance. This is the opposite prediction to the standard hypothesis in the literature that predicts that absence will affect performance adversely. Our prediction arises from an optimising framework in which choices are made with perfect information: at the margin, attendance is productive, but only up to the optimising point.

So far, we have assumed that factor inputs are independent. But suppose now that, *ceteris paribus*, the marginal product of attending class is positively correlated with ability: that is, $\frac{\partial^2 p}{\partial c \partial r} > 0$. This case is represented in Figure 1c, where the mpc for more able students, mpc_2, lies above that of the less able, mpc_1. The result is that the more able students will optimally choose to miss fewer classes: $t_{c2}^* > t_{c1}^*$ in Figure 1c. In an environment in which class attendance is voluntary, performance will be greater for the more able students and, hence, will be negatively associated with absence from class. Of course, mpq may also be positively correlated with characteristics captured by r. In this case, the relative sign of

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$t_{c2}^{*} - t_{c1}^{*}$ (and hence the association between performance and absence) will be ambiguous: it will depend on comparative advantage; that is, the relative correlation of r with mpc and with mpq.

In an econometric estimation of the effects of absence on performance, correlation between r and either of the other arguments – c, q – in the education production function given by equation (1) could potentially generate endogeneity bias if r is not perfectly observed. If more able students are less likely to be absent from class – $t_{c2}^{*} > t_{c1}^{*}$, as in Figure 1c above – then the estimated adverse effect of absence on performance will be biased upwards, in absolute terms, through endogenous selection and the resulting ability bias. The empirical investigation of the effects of absence from class on performance should be constructed so as to allow for heterogeneous effects of this sort. This observation lies behind the design of our later estimation strategy. In the case in which $t_{c2}^{*} < t_{c1}^{*}$, then the direction of endogeneity bias will be downward – but, again, the effects will be heterogeneous.

As we have seen, ability differences across students can affect absences from class through their influence on the educational production function, equation (1). But suppose now that there are differences across students in the time endowment for study, $\bar{t}$. In Figure 1d, we consider the effects of an exogenous reduction in the amount of time available for study activity: $\bar{t}$ falls from $\bar{t}_1$ to $\bar{t}_2$. In this case, there will be an increase in the number of classes missed together with an associated reduction in performance. In the model, the total time endowment for study, $\bar{t}$, is taken as exogenous. In reality, $\bar{t}$ is likely to be influenced by various arguments. For example, students from economically less advantaged backgrounds may be more likely to have to engage in part-time labour market activity, thereby reducing $\bar{t}$. The study time constraint may also be related to student ability, and hence to r in equation (1). If, for example, more able students undertake more non-curricular

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activities, then $\bar{t}$ will be negatively correlated with ability. In this case, more able students will be more likely to miss class. Note also from Figure 1d that the effect of missing class will be greater for more able students as $mpc_2^* > mpc_1^*$. Again, unobserved differences in ability across students will generate a bias in the estimate of the effect of absence on performance as part of the association between absence and performance is being explained by a differential propensity of the more able to be absent from class.

In summary, we have seen that, in an optimising framework, the theoretical effect of absence on performance is ambiguous. If class attendance is compulsory and students differ only in a randomly-distributed propensity toward compliance, then absence will have a positive association with performance as the less compliant will be more likely to adhere to the optimal number of classes. If, on the other hand, students are heterogeneous in ability then they will be likely to choose different optimal levels of class attendance: if ability is associated with a comparative advantage in class attendance – as in Figure 1c – then the more able will have a higher attendance rate and absence will be associated with poorer educational performance. Ability might also be correlated with the study time endowment: if more able students have a higher opportunity cost of studying, then it is likely that they will attend fewer classes. In this case, absence will be likely to have a positive association with performance. Estimation of the effects of absence on performance will be biased if ability is not observed or accurately proxied: the direction of bias will depend on the relative dominance of factors of the type we have identified. Finally, the model predicts that the magnitude of any effects of absence on performance will vary with student ability: if, for example, ability is relatively highly correlated with productivity of class attendance then the negative effect of absence on performance will be greatest for the more able students. These considerations inform our choice of empirical estimation strategy.

The model we have outlined so far assumes that students have sufficient information to be able to select their optimal level of class attendance. In reality, this is unlikely and students will make mistakes, attending either more or fewer classes than would be privately efficient. If students systematically under-estimate the marginal product of class attendance, then absence will tend to have an adverse effect on performance. This tendency might also be correlated with ability, so that less able students miss more classes and suffer a further reduced level of performance.

Informed by this contextual optimising framework, our empirical strategy will involve: first, an analysis of the factors associated with being absent from class; second, a simple, or 'naïve', analysis of the association between student performance and student absence from class; third, an attempt to identify causal effects of absence from class on student performance; and fourth, an investigation of whether or how any effects vary systematically with student characteristics, such as those associated with ability. The following sections describe the data and the econometric strategy for investigating these and related issues.

4. Data description and summary statistics

This paper uses administrative data from the Department of Economics at A UK University, collected over a three year period, in order to investigate the association between absence from class and student performance. Our data relates to 134 (159) [151] Economics and Industrial Economics students in the 2nd year of their three-year undergraduate degree who commenced their studies in October 2003 (2004) [2005].

4.1 Institutional context

The overall degree classification of students depends equally upon their performance in their 2nd and 3rd year, during which time they take 8 subject-modules (four in each year) – the 1st year is simply a pass/fail year determining whether students progress into their 2nd year of study. In their 2nd year, students take three compulsory (or core) Economics modules. For students on the BSc Economics degree these are a module in; Macroeconomics (Macro), Microeconomics (Micro) and Econometrics (Etrix). For students on the BSc Industrial Economics degree the core modules are a combined Macroecnomics and Microeconomics module (Econ), Industrial Economics (Ind), and either Economic Statistics and Econometrics (ESE) or Econometrics (Etrix). All students additionally take an optional subject-module from either within the Department or from a list of non-Economics modules.

All compulsory Economics modules are examined by a 3-hour summer written examination worth 80% and two pieces of assessed work (worth 10% each). In each module, tutorial classes are small group meetings held to complement lectures and focus on an exercise sheet or discussion sheet given out by the lecturer of a particular course. These classes are given for all compulsory 2nd year modules and attendance is regarded as compulsory. Students are allocated to their classes by the Department and this is mainly done on an alphabetical basis, with an adjustment for the 4th module option of the student in order to avoid clashes. Classes are held every week in the ESE and Etrix modules (a total of 20 classes in the academic year), but are held less frequently in Ind (12 classes), Macro (13 classes), Micro (16 classes) and Econ (16 classes). In each class, the tutor takes a register for that class and this information is then recorded electronically. The students are sent reminders about their tutorial time and location on the first and second absences (for each module).[4] A

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[4]   The database distinguishes between condoned absences due to for example, illness and/or having to attend

3rd absence requires the student to see their personal tutor and a 4th absence means the student must see the Director of Undergraduate Studies. After the 4th absence the student is put on report and a record of their attendance across <u>all</u> of their modules is monitored weekly. The Department can seek to have a student's registration withdrawn from the University for persistent non-attendance at tutorial classes, although this did not happen over the period under analysis.[5]

We focus exclusively on 2nd year students in this paper for two reasons. First, we wish to analyse the behaviour of students whose motivation is likely to be to maximise their final score in each module and as the 1st year is simply a pass/fail year, this may well not be the case: first year students are more likely to satisfice than to maximise. Second, we do not include 3rd year students as 3rd year modules typically do not run classes alongside lectures.

4.2   Summary Statistics

Despite being compulsory, attendance falls well short of 100% though absence is not as 'rampant' as reported by Romer (1993). Figure 2 plots the cumulative distribution function for the proportion of total absences across the three core modules for our 444 students. From the figure we note that around 11% of students missed no classes and around one-fifth of the students missed less than 3% of their classes. The median person missed around 8% of their classes, while the 75th percentile student missed around 14% of their tutorials.

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an interview for an internship and uncondoned absences. In our empirical analysis we consider both types separately but find that the results do not vary across the two types, hence we combine the cases. Note that a student missing a scheduled class but attending an alternative class is not recorded as absent.

[5]   As attendance in optional modules is not necessarily recorded, we focus exclusively on performance and attendance within the 3 compulsory modules for either Economics or Industrial Economics students.

Table 1 presents summary statistics of the variables used in the analysis, for our 444 2nd year students across their three core modules, broken down by the proportion of total class absences in each module: 0%, (0-7.7%], (7.7-12.5%], (12.5,18.75%] and over 18.75%.[6]

On average, students missed about 11% of their tutorials and just over 70% of these were uncondoned absences. While approximately one-third of the tutorial classes had no absences, around one-fifth had more than 19% absenteeism, implying that about 3 students are missing from the typical class of 15 students in one-third of cases.

The average overall performance of students in their 3 core modules was 60.3% (made up of an exam average of 59.8% and an assessed average of 62.0%). In their 1st year these students obtained an average mark of 63%, with a mark in Maths of 68% and in Statistics of 64%. 12% of these students were required to resit at least one of their seven 1st year examinations.

Regarding information on the timetable of tutorials, we note that 10% of tutorials start at 9 o' clock and 74% are held on either Monday or Thursday, compared to only 36% on Tuesday, Wednesday or Friday. Based upon student evaluations of the tutor (undertaken on a scale of 1-5, where 1 is excellent and 5 is poor) the average mark for the tutor across all of their students on the 2nd year modules is around 1.96.

Of the 2nd year students, 34% are female and 32% are overseas (fee-paying). The breakdown by degree course shows that 91% were registered Economics, with only 9% taking Industrial Economics.

Looking at the figures broken down by the number of missed classes, overall performance in the 2nd year courses is lower for those students who miss more classes. In addition, the dispersion of marks around the mean mark tends to be slightly greater for those

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[6]   The bin values used on the percentage of absences ensure sufficient observations in each bin.

students who miss more classes. We observe that the 1ˢᵗ year performance was markedly stronger for those students who then did not miss any classes in their 2ⁿᵈ year. For example, the Maths and Stats 1ˢᵗ year mark for those who did not miss any classes in their 2ⁿᵈ year was at least 10 percentage points higher than those students who missed at least 19% of the classes. We note that students who have higher absences seem to have more morning classes.

Figure 3 plots the distribution of 2ⁿᵈ year performance in the core modules for those students who missed no classes and also for those who missed at least one class. We note that not only is the distribution of marks shifted towards the left for those students who missed at least one class, but the shape of the distribution is also different. However, these are raw data plots and we next turn to multivariate analysis that will account for the effect of absenteeism on the location and shape of the distribution.

5.   The Econometric Model

The data enable us to observe the performance and tutorial absence of students in each of their three compulsory 2ⁿᵈ year modules. With 444 students over three cohorts in each module, we have a panel of 1332 observations.

The dependent variable p in our model is the student's end-of-year performance measured as a score out of 100 for each of the student's three core modules. The main explanatory variable of interest is the proportion of tutorial classes missed during the second year of study, called *absence, a,* defined with respect to each of the three core modules.

We use the quantile regression (QR) framework to estimate the effect of absence, *a*, on performance, *p.*[7] Unlike the conventional least squares framework that looks at the effect on the conditional mean, the QR framework allows for differing effects of *a* on different parts

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[7]   For a comprehensive introduction to the topic, see Koenker (2005).

of the *p* distribution, thus enabling us to look at the effect of *a* on the location, scale and shape of the *p* distribution. This is consistent with the theoretical discussions provided in Section 3, where the personal characteristic is allowed to interact in a non-trivial way with *a* and other covariates to have an effect on *p*.

The θth ($0<\theta<1$) conditional quantile of the *p* distribution for the *j*-th module, $j = 1,2,3$, for the *i*-th individual ($i=1,..,444$) is specified as:

$$p_{ij} = \beta_0(\theta) + \mathbf{x}_{ij}{}'\boldsymbol{\beta}(\theta) + a_i\gamma(\theta) + v_i\,\delta(\theta) + \varepsilon_{\theta ij}; \quad \text{Quant}_\theta(\varepsilon_{\theta ij}\,|\mathbf{x}_{ij}) = 0 \qquad (3)$$

where $\text{Quant}_\theta(\varepsilon_{\theta i}|\cdot\,)$ denotes the θth conditional quantile of ε. v_i is an unobservable individual characteristic and we estimate this variable using a two-step method. The full set of additional controls used is discussed in the results section.

Step 1

We have absenteeism information on the three core modules for each individual *i*. Let a_{ij} be the proportion of tutorials missed by individual *i* in module *j,* where:

$$a_{ij} = z_{ij}\boldsymbol{\delta} + v_i + u_{ij} \qquad (4)$$

v_i is individual specific unobservable random effect. The observed a_{ij} generally lie between 0 and 0.69 with about 32% of the tutorials having zero absences and most of the students missing only up to about a third of the tutorials. Given the nature of our dependent variable *a*, we estimate the model as a Panel Tobit model. This model assumes that *u* is distributed as $N(0,\sigma^2{}_u)$ and the unobservable individual-specific effect *v* is distributed as $N(0,\sigma^2{}_v)$. As detailed in the Appendix, using this model, we obtain an estimate of v for each individual ($\hat{v}_i$) which is known as the empirical Bayes predictions or shrinkage estimate (Goldstein,

2003). We then use this $\hat{v}_i$ in place of v_i in equation (3). We use gllamm (2004) to obtain our estimates.[8]

Stata 9 was used to estimate the coefficients of our QR model. The standard errors were calculated by the bootstrap method using 500 replications which accounts for clustering at the individual level.

6. Results

6.1 Absenteeism

Table 2 reports the results of the random effects Tobit model based on the absenteeism variable, *a*. The timings of classes are used as instruments in order to identify the causal effect of absenteeism on performance as the students were randomly allocated to classes. Class times for these core modules are largely centrally timetabled to avoid timetable clashes.

The results suggest that students who performed well in their 1st year Statistics course tend to have lower absenteeism in their 2nd year. There are some interesting findings in terms of the information we have on the time of the tutorial class. We find that tutorial absence is markedly higher for the 9am class and to a lesser extent for all mornings classes (those starting before midday) compared to afternoon classes. There is no significant fall in absences in classes on Tuesday, Wednesday and Friday relative. We note that lower absence is associated with a lower (better evaluation) tutor score.

On personal characteristics, we find that female students miss fewer classes compared to male students. Overseas students are found to miss more classes compared to home (EU)

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[8] Results from a model where we use a random-effects ordered probit for the first stage in order to estimate the unobserved individual specific term produced very similar results and therefore not reported here. We also used a generalisation of the two-step method proposed by Buchinsky (1998, 2001) and included the generalised residual and its square from the first stage model estimates in the second stage quantile regression model. The results are not reported here since they were very similar to the results reported here.

students, holding all else constant. We find no difference in the attendance rates of Industrial Economics degree students compared to Economics students. Absence was higher in 04/05 than for the other two later cohorts. Attendance at classes varies significantly only for one of the subjects, with Etrix experiencing markedly greater absenteeism.

The variance of the individual-specific random effects is found to be significantly different from zero. A plot of the Bayesian estimate of the random effects $\hat{v}_i$ is given in Figure 4a. As expected, it is unimodal and centred around 0. Figure 4b plots the estimated random effects but now separately for students who had no absences in a particular module and for those who had at least one absence in a particular module. Interestingly, the density plot is shifted towards the negative part for those students who had no absences. This implies that these students have a characteristic which makes them less prone to absenteeism.

6.2   Performance

We consider two empirical models: (1) the benchmark models treating absenteeism as exogenous (Table 3 results), and (2) the models treating absenteeism as endogenous using the estimated unobserved individual-specific term as a control for endogeneity in the performance equation (Table 4 results). When we discuss these two empirical models, we present results from pooled ordinary least squares estimation (OLS) (Column [1]), Within Group Estimation (WG) (Column [2] in Table 3) and Instrumental Variable Estimation (using the predicted absences from the first stage panel Tobit model – Column [2] in Table 4) and Quantile Regression estimation (QR) (Columns [3] to [11]). The estimated effects of absences along with the 95% confidence intervals from the within group estimation and also the quantile regression models are presented in Figures 5A and 5B.

Prior to discussing the results from various estimations, we summarise what the various estimates may be telling us. Assuming that there is no heterogeneity in the effects of

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covariates on the performance, OLS would consistently estimate the penalty attached to missing classes on the conditional mean performance if there are no selection effects and there is no unobserved heterogeneity. On the other hand, if there is selection and if this selection can be adequately captured by allowing for the unobserved individual effect, WG estimation would provide consistent estimators. Now, turning to the QR model results, these models allow for a heterogeneous effect of the covariates on the various parts of the performance distribution.

We first discuss the results from Model 1, the models that treat absenteeism as exogenous, presented in Table 3. A cursory examination of the plot in Figure 5A suggests the presence of some heterogeneity in the effects of absences on performance. The penalty attached to missing classes is generally found to be smaller for high ability students. It is estimated that for students in the top 10% of the performance distribution being absent from 10% of classes is associated with around a 1 percentage point loss in the subject score, *ceteris paribus*, compared to about 2 percentage points for those students in the bottom 10% of the performance distribution. Interestingly, the penalty for missing classes is very much smaller on the conditional mean performance from the within group estimation. Also, we note that the OLS estimate is very similar to the estimate from the QR model at the median. Therefore, we conclude that there might be some effect of unobserved individual characteristics that needs to be accounted for. Comparison of WG with that of the QR model results indicates that not only might controls for unobservables be relevant, but also that some allowance for heterogeneous effects of covariates on different parts of the performance distribution is important.

Results for other variables included in the model are also informative. We find that females perform worse than males and that this negative effect is increasing across the quantile index. While this result might be viewed as surprising, McNabb *et. al.* (2002) find

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that while, on average, females perform better than males at University, they are significantly less likely to obtain a first class degree than males. Given that the criteria for admission into the Department of Economics is AAB at A-level (or equivalent),[9] we are by definition observing already high performing individuals.

The coefficients on variables reflecting 1st year performance are as expected, although, in general, these do not show much variation across the quantiles. More interestingly, we find that the effect of the tutor score variable is negative, with students performing better in classes where the tutor has a lower score (better evaluation), although this negative effect becomes smaller across the quantile index.

We next turn to the models that allow for the possibility of endogenous selection in the number of classes the student chooses to attend, presented in Table 4. The IV results (Column [2]) are very similar to the OLS results reported in Table 3 (Column [1]), with exogenous absenteeism, where being absent from 10% of classes is associated with around a 1.6 percentage point loss in the subject score, *ceteris paribus*. For the models presented in Columns [1], and Columns [3]-[11] an estimated 'individual specific characteristic' variable is included, although this variable is only significant in the bottom half of the distribution. While the coefficient estimates on most of the covariates are again very similar in terms of magnitude and significance to those reported in Table 3, the coefficient estimates on the absence variable are markedly reduced. Interestingly, we now find that the effect of missing classes is only estimated to be significant for high 'ability' students. Missing 10% of classes is estimated to be associated with around 1-2 marks for this group of students. The estimated effect of missing class for the low 'ability' students is insignificantly different from zero when selection is accounted for in the estimation.

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[9]   A-levels are graded A through to E, with A being the top grade.

In summary, when we take into account that individuals might be self-selecting to miss class, we find there is a penalty attached to absence - but only for more able students. The fact that the estimated effects of absence on performance are less negative in the endogenous than in the exogenous model is consistent with our theoretical discussion of Figure 1c where we predicted a negative ability bias – and hence that ability disproportionately raises the marginal product of class attendance, relative to its effect on the marginal product of other forms of study. That the average effect of absence on performance is still negative in the endogenous model suggests that there is no particular excess supply of classes – the case presented in Figure 1a, in which the causal effect of absence on performance would be positive. Similarly, the case presented in Figure 1d – in which more able students allocate less time to total study effort – is not supported. Instead, to the extent that we are correcting fully for ability bias, the results indicate that absences have a negative causal effect on performance: this is consistent with the case presented in Figure 1b, with the implication that the number of classes offered is fewer than the student's optimising number. We note, however, that the quantile results for the endogenous model show that the significant negative effects of absence on performance hold only for upper quantiles. This is consistent with a combination of the cases depicted in Figures 1b and 1c, with more able students attending more classes than the less able (Figure 1c) and with this optimal number - for the more able only - being greater than the number provided (as in Figure 1b).

7. Concluding remarks

There is now a significant body of work which attempts to delve inside the educational 'black box' in order to deepen the understanding of the processes by which human capital is acquired in learning environments. Much of this work has focused on the importance of factors such as class size and peer effects and has concentrated on educational attainment of pupils in compulsory schooling, with less attention paid to higher education This is surprising

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given that there has been a growing policy focus on higher education, with governments in many countries viewing the university sector as an important driver of research, development and growth. The nature of higher education is likely to be fundamentally different from compulsory primary and secondary education, with greater student autonomy in study in higher education. Our attention in the current paper has focused on the causal impact of class absence on student performance and on variations in the estimated effects according to particular student characteristics. The analysis has also incorporated a study of the determinants of class absence.

Our empirical analysis makes use of rich administrative panel for economics students at a UK university. We have exploited a number of key features of the data-set: (i) the panel nature of the data enables us to control for unobserved heterogeneity across students and hence for endogeneity between attendance and performance stemming from the likely influence of effort and ability on both; (ii) random assignment of students to classes avoids the potential endogeneity problems that occur when students can self select into classes; (iii) information on the time slots of the classes in the student's weekly timetable serves as a source of exogenous variation in a student's absence and hence yields potential instruments for the identification of a causal effect of absence on performance.

Our theoretical framework has outlined various possible links between absence and performance and how these might vary with student characteristics such as ability. The approach predicted that absence rates will be lower for more able students in the case in which ability is relatively highly correlated with the marginal productivity of class attendance rather than with other factors in the educational production function. We find empirical support for this prediction as, on average, absence is lower for students with better prior performance – a proxy for ability. In this same case, the model also predicted a negative relationship between absence and performance: both because of selectivity bias and because

the marginal product of attendance is greater for more able students. The implications are that: we should find a negative association between absence and performance; that this negative effect should be moderated when we correct for endogenous selection; and that the causal negative effect should be stronger for more able (and hence better-performing) students.

We have reported results consistent with each of these predictions, from which we conclude that a major driver of patterns in class attendance are differences in productivity of class attendance across students. In the absence of controls for unobserved heterogeneity, we find that there is a significant effect of class absence on the student's performance. This effect is weakened – though remains significant – when controlling for unobserved individual effects. We interpret this as consistent with the presence of ability bias in the naïve regression which fails to model the endogenous nature of absence and performance. In a quantile regression specification, it emerges that the adverse effect of missing class is greater for better-performing students, consistent with our hypothesis that effects are likely to vary with factors such as student ability.

What are the policy implications of our findings? We think that there are several. First, the evidence is consistent with the view that class attendance is a productive activity – the estimated causal effect of missing class is negative. Second, theory suggests that grade-maximising students might optimally choose to miss classes and hence that making classes compulsory could be inefficient. However, there is no evidence that missing class is associated with better performance, as would be implied in the model with compulsion and excess classes: compulsion does not seem to be creating problems – the administrative regime seems sufficiently flexible as to permit optimising choices by students. Third, the evidence suggests that class attendance is particularly productive for better-performing students: perhaps additional, voluntary classes could be organised with these students in

mind. Alternatively, it might be appropriate to reflect on the nature of the teaching and learning characteristics of classes with a view to enhancing their effectiveness for weaker students.

Appendix

<u>Bayesian estimate of the random effects</u>

v_i is the unobserved individual specific random effects in the model (see equation (2)). Then,

$f(v_i/data) = f(v_i/a_{i1}, a_{i2},...,a_{im}) = f(a_{i1}, a_{i2},...,a_{im}/ v_i)f(v_i)/ f(a_{i1}, a_{i2},...,a_{im})$

Thus,

$$E\left(v_i \mid a_{i1},...,a_{im}\right) = \int v_i\, f(v_i \mid a_{i1},...,a_{im})dv_i$$

$$= \frac{\int v_i\, f(a_{i1},...,a_{im} \mid v_i)f(v_i)dv_i}{f(a_{i1},...,a_{im})}$$

$f(a_{i1},...,a_{im} \mid v_i)$ is the conditional likelihood and $f(a_{i1},...,a_{im})$ is the marginal likelihood which are obtained during the maximising of the likelihood function. The estimated $E\left(v_i \mid a_{i1},...,a_{im}\right)$ is known as the Bayesian shrinkage estimator.

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Figure 2: CDF of proportion of absences across 3 core modules
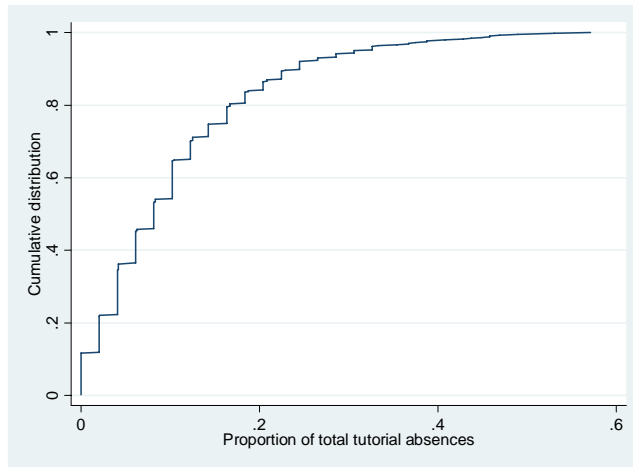
Figure 3: Total Marks in Core 2nd Year Modules

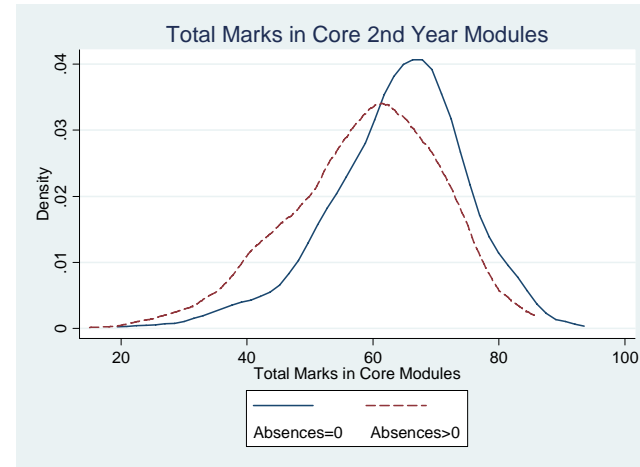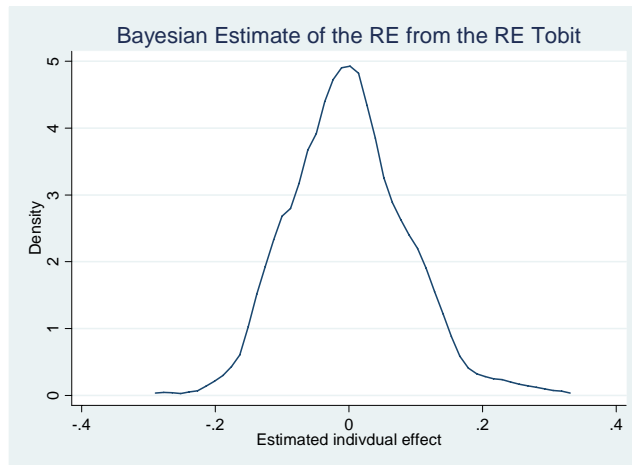**Figure 4A: Bayes Estimate of the Individual Unobservable Effect**

Figure 4B: Bayes Estimate of the Individual Unobservable Effect: by absenteeism

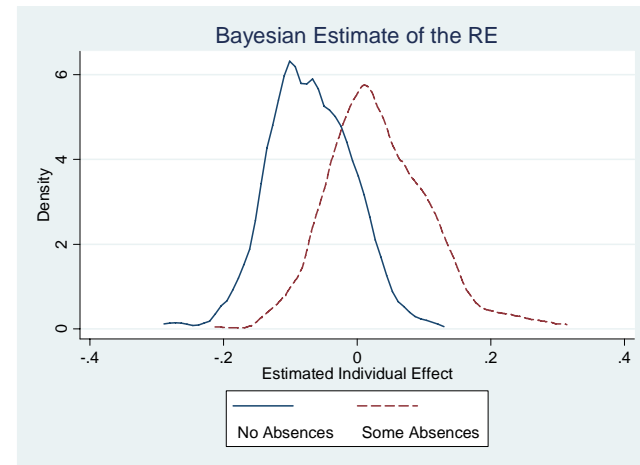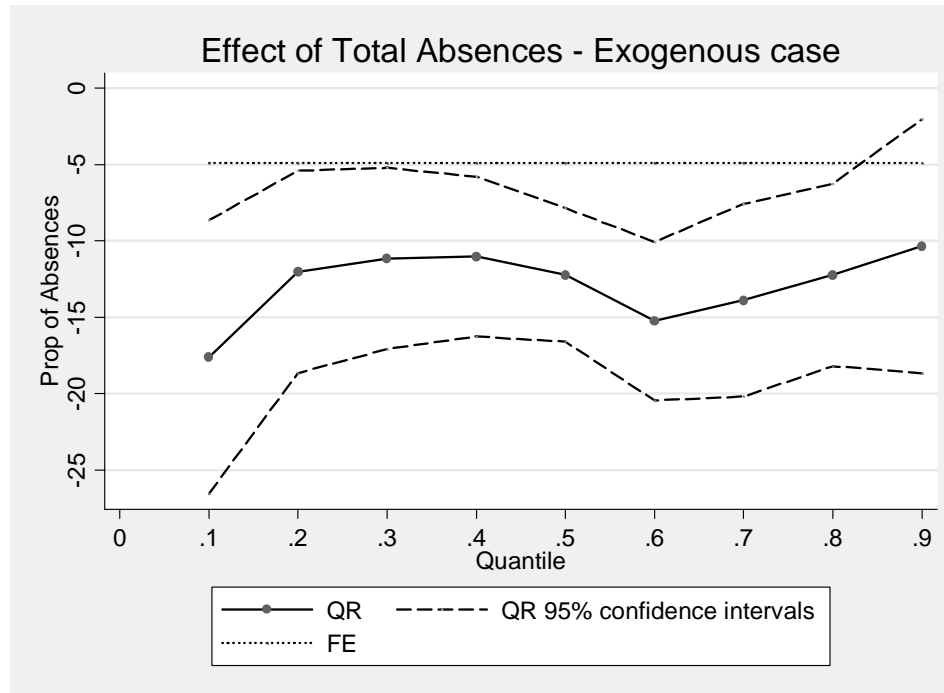**Figure 5A: Effects of Absence on Performance**
(Exogenous)

Effect of Total Absences - Exogenous case

Figure 5B: Effects of Absence Performance
(Endogenous - Bayesian Estimate of Unobserved Effect)

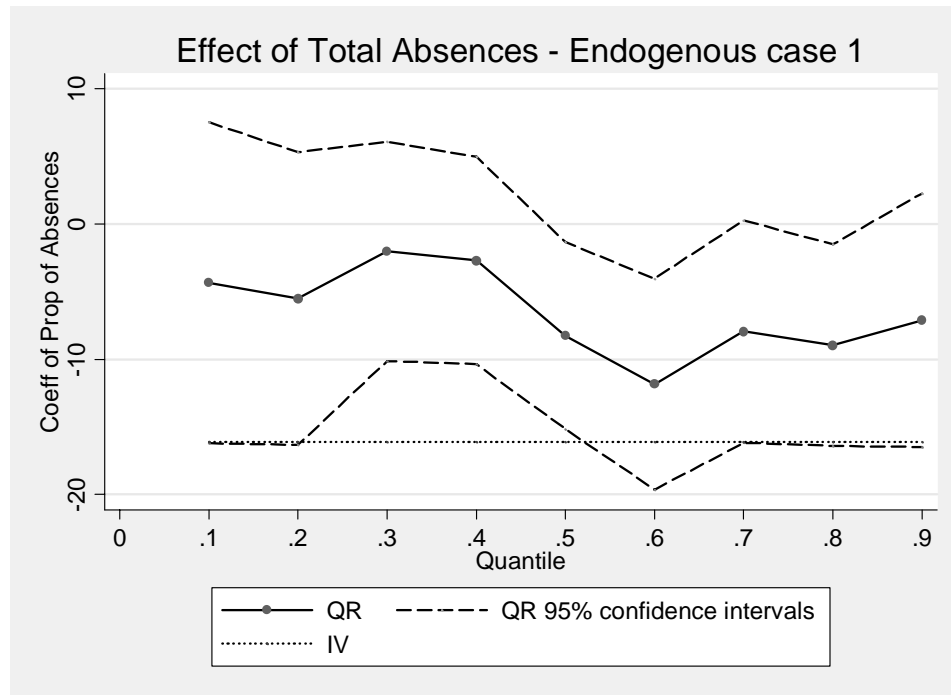Effect of Total Absences - Endogenous case 1

Table 1: Summary statistics across all subject modules and by proportion of total absences

	All		Number of Absences =0		Proportion of Absences % (0, 7.7]		Proportion of Absences % (7.7, 12.5]		Proportion of Absences (12.5,18.75]		Proportion of Absences >18.75%	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2nd year performance												
Total (average)	60.33	11.86	63.82	10.80	61.71	10.81	60.73	12.09	55.81	11.53	55.14	12.40
Exam (average)]	59.86	13.31	63.41	12.34	61.42	12.31	60.42	13.53	54.95	12.97	54.51	13.78
Assessment (average)	62.04	10.85	65.17	9.60	62.97	9.50	61.37	11.42	59.22	10.59	57.64	12.41
1st Year Marks												
Maths	68.01	15.46	72.00	14.42	68.76	13.49	67.14	16.54	64.75	14.90	62.78	17.25
Stats	64.05	15.48	69.42	14.91	65.79	14.12	62.71	15.02	59.59	14.18	56.17	15.21
Other Total Average	62.46	8.38	64.75	8.21	62.92	7.56	61.23	8.73	60.73	7.73	59.81	8.84
Resit dummy	0.12	0.32	0.09	0.28	0.07	0.26	0.13	0.34	0.13	0.34	0.21	0.41
Tutorial Information												
Proportion of Total Absences	0.11		0.00		0.06		0.11		0.16		0.31	
Proportion of Uncondoned Absences	0.08		0.00		0.04		0.07		0.12		0.24	
Proportion of Classes with 0 absences	0.32											
- Classes with (0, 0.077] absences	0.24											
- Classes with (0.077, 0.125] absences	0.12											
- Classes with (0.125, 1875] absences	0.13											
- Classes with (0.1875, max] absences	0.19											
Tutor score [1=highest,…5=lowest]	1.93	0.54	1.88	0.53	1.92	0.54	2.07	0.50	1.90	0.55	1.96	0.55
Tutorial Timings [base: Monday, Thursday pm]												
9:00am tutorials	0.10		0.10		0.11		0.07		0.09		0.13	
Other morning tutorials [excl 9:00am tutorials] + 17:00 hours	0.56		0.53		0.52		0.57		0.61		0.62	
Tuesday, Wednesday , Friday tutorials	0.35		0.36		0.36		0.30		0.38		0.35	

	All		Number of Absences =0		Proportion of Absences % (0, 7.7]		Proportion of Absences % (7.7, 12.5]		Proportion of Absences (12.5,18.75]		Proportion of Absences >18.75%	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Other characteristics												
Industrial Economics Degree (IndEc)	0.09		0.06		0.04		0.15		0.11		0.12	
2nd Year Modules [base: Microeconomics]												
Macroeconomics (Macro)	0.30		0.38		0.34		0.00		0.34		0.30	
Microeconomics (Micro)	0.30		0.31		0.31		0.40		0.29		0.23	
Econometrics (Etrix)	0.32		0.26		0.31		0.48		0.28		0.37	
Economic Statistics and Econometrics (ESE)	0.01		0.00		0.00		0.04		0.01		0.03	
Economics (Econ)	0.03		0.02		0.03		0.04		0.04		0.03	
Industrial Economics (Ind)	0.03		0.03		0.00		0.05		0.04		0.04	
Female	0.34		0.37		0.38		0.32		0.37		0.24	
Non-UK fee student	0.32		0.29		0.29		0.33		0.32		0.43	
Cohort 04/05	0.30		0.24		0.27		0.31		0.34		0.42	
Cohort 05/06	0.36		0.41		0.34		0.39		0.37		0.26	
Number of Observations	**1332**		**429**		**326**		**166**		**174**		**237**	

Table 2:

Random Effects Tobit Model for Tutorial Absences

Variable	Coefficient Estimate
1st Year Marks	
Maths	-0.000
Statistics	-0.003***
Other	-0.001
Resit dummy	-0.008
Tutorial info (2nd year)	
9am class	0.079***
Other morning tutorials [excl 9:00 tutorials] + 17:00 hours	0.040***
Tue, Wed, Fri class	-0.001
Tutor Score	0.026***
Personal characteristics	
Cohort 04/05 [base 06/07]	0.048***
Cohort 05/06	-0.024***
Female	-0.027**
Overseas	0.052***
IndEc	0.047
2nd Year Modules	
Macro	0.003
Econometrics	0.028***
Economic Statistics & Econometrics	-0.039
Economics	-0.029
Industrial Economics	-0.057*
Intercept	0.241***
σ_α (std. Error) [unobserved heterogeneity std dev]	0.103***
σ_u	0.101***
Proportion of error variance attributed to unobs heterog	0.510
Log Likelihood	246.69
Number of Individuals	444
Number of Observations	1332
Number of left censored Observations	429

Table 3: Exogenous Absenteeism Model

	OLS	Within Group	Quan 0.1	Quan 0.2	Quan 0.3	Quan 0.4	Quan 0.5	Quan 0.6	Quan 0.7	Quan 0.8	Quan 0.9
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Absences[a]	-13.40***	-4.92*	-17.61***	-12.03***	-11.15***	-11.03***	-12.23***	-15.26***	-13.89***	-12.24***	-10.35**
Cohort (04/05)	-4.26***		-6.23***	-4.98***	-4.11***	-3.181***	-3.821***	-3.471***	-3.91***	-3.78***	-3.97***
Cohort (05/06)	-2.69***		-4.39***	-2.82***	-2.48***	-2.27***	-2.17**	-1.69**	-1.50*	-1.16	-0.11
IndEc	0.00		0.83	-1.41	-0.27	0.22	0.15	1.06	0.17	0.38	0.36
Female	-2.14***		-1.71	-0.99	-1.60*	-1.16	-1.37*	-1.73**	-1.96***	-2.24***	-2.35***
Oversees Fee	-1.61**		-2.08	-3.30***	-2.60**	-2.26***	-2.17**	-1.13	-1.18	-0.96	-0.48
1st Year Marks											
Maths	0.07*		0.09	0.12***	0.12***	0.10***	0.10***	0.09**	0.05	0.03	0.01
Stats	0.25***		0.29***	0.24***	0.24***	0.25***	0.25***	0.24***	0.24***	0.24***	0.19***
Other	0.37***		0.30***	0.40***	0.40***	0.36***	0.34***	0.32***	0.33***	0.33***	0.35***
Resit dummy	1.00		0.37	0.95	0.49	-0.01	0.81	0.79	0.40	1.55	2.34
2nd Year Modules											
Macro	-0.82	-1.15**	3.69***	1.98*	0.28	-0.43	-2.16**	-2.81***	-3.62***	-4.48***	-4.95***
Etrix	4.13***	3.83***	9.64***	9.28***	6.81***	5.33***	3.03***	2.18***	0.91	-0.43	-0.86
ESE	5.65*	4.60	4.01	8.99	3.55	4.48	5.47	8.57	8.46	5.76	3.29
Econ	3.53*	3.41*	6.34**	7.28**	3.65	1.62	1.48	1.30	0.93	-0.59	-2.22
Ind	9.36***	9.33***	15.50***	14.71***	11.23***	8.30***	7.79***	4.98**	4.97**	1.96	-0.69
Tutor Score	-0.95**	-1.54***	-1.29	-2.05***	-1.92***	-1.54**	-1.04*	-0.92	-0.52	-0.19	-0.13
Intercept	22.34***	62.53***	10.56*	9.92**	13.59***	18.46***	22.74***	27.22***	31.44***	35.39***	40.84***

Notes: (a) Absences is the proportion of missed tutorials (both condoned and uncondoned). (b) *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 4: Endogenous Absenteeism Model (Using Bayes' estimate of the individual effect)

	OLS	IV	Quan 0.1	Quan 0.2	Quan 0.3	Quan 0.4	Quan 0.5	Quan 0.6	Quan 0.7	Quan 0.8	Quan 0.9
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Absences[a]	-6.63**	-16.10***	-4.34	-5.51	-2.03	-2.7	-8.25**	-11.84***	-7.95*	-8.96**	-7.12
Cohort (04/05)	-4.48***	-3.99***	-6.92***	-5.37***	-4.01***	-3.59***	-3.60***	-3.70***	-4.17***	-3.87***	-4.21***
Cohort (05/06)	-2.58***	-2.85***	-4.39***	-3.22***	-2.50***	-1.93**	-2.13**	-1.66*	-1.24	-1.1	0.13
IndEc	-0.43	0.13	-1.00	-1.08	-2.43	-0.12	-0.44	0.54	-0.42	0.14	-0.33
Female	-1.96***	-2.24***	-1.73	-1.17	-1.32	-1.14	-1.18	-1.64**	-1.84***	-2.24***	-2.38***
Oversees Fee	-1.87**	-1.31	-3.19**	-3.56***	-3.17***	-2.63***	-2.08**	-1.3	-1.53*	-1.01	-0.79
1st Year Marks											
Maths	0.07*	0.06*	0.11**	0.12***	0.12***	0.10***	0.09**	0.09**	0.05	0.04	0.02
Stats	0.26***	0.23***	0.30***	0.26***	0.25***	0.27***	0.25***	0.25***	0.26***	0.25***	0.20***
Other	0.37***	0.36***	0.29***	0.40***	0.41***	0.36***	0.34***	0.31***	0.33***	0.32***	0.35***
Resit dummy	0.99	0.78	0.75	0.93	0.37	0.03	0.63	0.51	0.42	1.31	2.42
2nd Year Module											
Macro	-0.83	-0.84	4.09***	1.59	0.77	-0.63	-2.50**	-2.93***	-3.24***	-4.52***	-4.98***
Etrix	4.07***	4.32***	10.42***	8.79***	6.98***	5.00***	2.90***	2.17***	1.07	-0.64	-0.91
ESE	6.08*	5.69*	4.78	8.64	7.59	5.5	4.19	9.77*	8.99*	5.90	3.90
Econ	3.92**	3.39*	9.38***	6.70**	6.32*	1.88	1.95	1.75	1.23	0.01	-2.04
Ind	9.81***	9.07***	18.28***	14.53***	13.40***	10.17***	7.85***	5.42**	5.65**	2.12	-0.19
Tutor Score	-1.00**	-0.77	-1.45*	-2.00***	-1.64**	-1.97***	-1.05*	-1.03*	-0.48	-0.31	-0.09
Est Ind Effect	-11.13**		-20.81**	-10.89	-13.52**	-13.34**	-8.58	-4.78	-7.08	-3.86	-6.89
Intercept	20.67***	23.80***	7.81	8.26**	10.32**	17.73***	22.69***	26.83***	29.53***	34.76***	39.66***

Notes: (a) Absences is the proportion of missed tutorials (both condoned and uncondoned). (b) *** significant at 1%, ** significant at 5%, * significant at 10%.
(c) Column [2] uses the predicted absences from a first stage random effects Tobit model as an instrument for Absences.