Who goes to lectures (and does it matter)?

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Using a combination of survey and student record data from a first year university economics principles class, we look at the characteristics of students who are attending face-to-face lectures, versus those students who choose to view these same lectures via online lecture recordings. The survey includes the Biggs (2001) Revised Study Process Questionnaire (SPQ) on 'deep' versus 'surface' learning methods, which we use to see how these different learning approaches may be related to attendance at lectures. The econometric evidence presented here suggests that lecture attendance is positively affected by whether or not the student employs a deep approach to learning. There is also some evidence that students treat face-to-face lectures and viewing these lectures online as substitutes, rather than complements, to learning. We end with some tentative evidence on whether the chosen mode of lecture delivery ultimately makes a difference to a student's final mark in the unit.

Keywords: applications in subject areas; evaluation methodologies; post-secondary education; teaching/learning strategies.

Introduction and review of literature

Attendance at lectures has been an issue across university disciplines for many years. Romer (1993) asked the pointed question of why, given the opportunity cost of not attending lectures was potentially so high (in terms of lost future earnings), they were still quite poorly attended. Back in 1993 (and before) this question was particularly pertinent, because if a student missed a lecture, the best they could do was copy written notes of the lecture from a classmate, and so the information received was an imperfect substitute for the lecture itself.

However, today the issue is a slightly different one, because technology has enabled students to miss lectures but, through online audio and/or visual lecture recordings, still receive the same content as those who were physically there. Moreover, students can use a 'blended learning approach', using a mixture of the two forms of content delivery. In other words, this is not a straight binary decision for students to use one *or* the other method. Given this, the focus has turned towards looking at which type of learning approach (online, face-to-face, or a mix of the two) has the most beneficial impact on students.

It has been argued that presenting information in the visual and auditory modalities (simultaneously) results in superior learning (Owston *et al*, 2011). This is supported by 'media richness theory' (Bassili, 2008) that takes into account the differences in students' attitudes and preferences and explains why some students might prefer to go to lectures or only watch the online lecture, whilst others might be more inclined to go to live lectures and listen to the recorded lecture for revision. The 'media richness theory' also predicts that differences in students' attitudes are related to the perceived ambiguity and difficulty of the content of the units they are learning. Students are more inclined to attend live lectures if they expect the learning content to be difficult and otherwise they choose the alternatives (see Owston *et al*, 2011 and Bassili, 2008). Web-based lectures are believed to provide flexibility (for example, mature aged students who are more likely to be involved in paid employment, child care or other carer responsibilities), equity of access, ease of engagement (Johnston *et al*, 2012), or as an emergency alternative for an enforced absence (Kinlaw *et al*, 2012).

Web- based lectures also provide an ongoing revision tool, a flexible means of engaging with lecture content, particularly for units with a high proportion of non-English speaking students (Scutter *et al*, 2010) and accommodates learning experiences for a variety of students with different abilities and preferences (Lancaster *et al*, 2011). Cooke *et al* (2012) argue that podcasting lecture content could assist first year students in adjusting to university life. Johnston *et al* (2012) show that almost 96per cent of enrolled students (in undergraduate nursing) support the provision of online lectures in addition to live lectures (but not as a replacement). Vernadakis *et al* (2012) show blended learning methods provide students with more control over their learning and foster critical thinking, which eventually has a positive impact on student learning outcomes. In their research they indicate that almost 56 per cent of students rank 'an ability to hear the lecture again' as the most useful aspect of the podcasts. 46 per cent used the podcasts for exam revision and 49 per cent enjoyed the flexibility of listening to podcasts anywhere they liked. Crook *et al* (2012) highlight the enhancing role of video technology in the provision of assessment-related feedback and consequently higher engagement of staff and students in this process. In their research, almost 80 per cent of students voted in favour of the use of video feedback, as they considered it as a facilitator of a prompt generic feedback in a more engaging and flexible manner.

Despite all these purported advantages arising from blended teaching methods, the relation between usage of a virtual learning environment and students' performance and learning outcomes is not clearly understood. Stricker *et al* (2011) and Williams *et al* (2012) argue that online learning is beneficial to students who use these resources as a complementary resource. Supplementary use of web- based resources is likely to result in an average increase in quizzes and examination marks. Other studies (Johnston *et al,* 2012; Cooke *et al,* 2012; Gomez and Igado, 2008; Zubas *et al,* 2006) indicate that students' performances in blended courses was equivalent or slightly superior to traditional courses, whilst some find a very weak relation between access to the recorded lectures and students' performance. Important concerns have been raised about students' attendance and engagement when lectures and supplementary resources are available online (Scutter *et al* 2010, and Kinlaw *et al* 2012). Lyons *et al* (2012) show the perceived positive learning experiences of students are affected by the level of their technological knowledge and confidence to navigate the online class environment. Kinlaw *et al* (2012) show in-class activities are the main motivations for student to attend class and when these activities are replaced by online alternatives around 30 per cent of students are less likely to attend class and the 'voluntary absence rate' will be higher (see also Traphagan *et al*, 2010). They also suggest students are using recorded lectures significantly more prior to exam dates which, coupled with poor lecture attendance, may reflect that this viewing is the first engagement of these students with lecture content. (Johnston *et al*, 2012).

With respect to the advantages of attending lectures versus viewing these lectures online, Stanca (2006) found a statistically significant effect from attending lectures; however, this still translated into a relatively modest improvement in overall academic performance. If a student attended all lectures, rather than making the mean attendance, their final grade would have been only around 1-1.5 percentage points higher. He also found a modest positive effect on final marks for those students in a quasi-experiment comparing those who attended the actual lectures with those who were only allowed access to the lecture recordings. Figlio *et al* (2010) found that those viewing only the online lecture recordings ultimately performed better than those restricted to just the live lectures. McNulty *et al* (2011) also noted a negative correlation between medical students who accessed video recordings of lectures and their ultimate academic performance. Others again (Brotherton and Abowd, 2004; Bell *et al*, 2001) found no statistically significant difference in the grades obtained by the online versus face-to-face groups of students. In terms of studies focussing on a blended approach, von Konsky *et al* (2009) provide some evidence that, whilst lecture attendance was roughly the same across all grades, passing students were more likely to use lecture recordings as a supplement to their lectures. Wieling and Hofman (2010) purported to find a strong substitution effect between face to face and online lecture recordings. Students who attended most or all of the lectures face to face received no additional benefit from viewing lectures online. However, Williams *et al* (2012) show that students attending the majority of lectures actually got more benefit from also accessing the online recordings than students who attended fewer lectures, and so were using these online recordings as substitutes.

It appears from the literature, therefore, that finding a definitive answer to the question on the efficacy of lecture attendance is quite difficult. Empirically, this is understandable. From an econometric perspective, lecture attendance is undoubtedly endogenous to final academic performance. Students who attend more lectures are (possibly) also more likely to be motivated students, who put in greater effort. Therefore, one might observe a statistically significant relationship between attendance and final grades, but that may be due to the fact that these students work harder, and it is this additional effort, rather than the lectures *per se*, that is leading them to have higher marks. One way of dealing with this (which we use in this paper) is to find appropriate instruments for lecture attendance. In theory, if one could find appropriate instruments that are correlated with lecture attendance, but not with final academic performance, then the instruments can 'net out' the correlation of student effort with attendance, leaving only the effect of the actual lecture on final performance. The key, of course, is in finding 'appropriate' instruments. Stanca (2006) for example, used travel time to university, hours worked in paid employment and home access to the internet as instruments for attendance. However in this study these instruments were found to perform quite poorly. Stinebrickner and Stinebrickner (2008) and Kirby and McElroy (2003) also used an IV estimation to control for the endogeneity of attendance.

This paper, therefore, is a modest attempt to further our knowledge of, first, the characteristics of students attending lectures, and second whether, once we control for a large number of other factors, this attendance has a positive effect on a student's overall academic performance. The paper is arranged in the following manner. First we outline the data used in this study, as well as some initial analysis of these data. The following section describes the econometric methodology we are applying to the data, as well as a discussion on the results we obtain from this estimation. The final section is a conclusion.

Data

This analysis uses data taken from a first year Microeconomics Principles class at the University of Western Australia from the first semester of 2012. All face-to-face lectures are recorded using the *Lectopia* recording system and available for students to stream or download within an hour of the actual lecture. There were 26 lectures in this unit for the semester. To get as much information as possible for our analysis we have taken data from three sources:

> A student survey, conducted during tutorials in the final week of the semester. The survey covered a range of issues that looked at what one might call the first year 'experience'. Students were asked a number of questions relating to different aspects of their university experience, including questions on: their personal characteristics (gender, birthplace, age, whether living at university colleges, or with parents, and so on); education information (prior education, including whether they had studied economics before); their experiences at university (a series of questions on their degree of satisfaction with their university life, what their biggest problems were in the transition from high school and so on); study habits (including hours per week of study, how many face-to-face lectures they attended, plus several questions on their use of lecture recordings); and the revised 20 question Study Process Questionnaire, developed by Biggs (1987). These questions were designed to assess the students' approach to learning (surface versus deep).
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> Student records data, in order to obtain data on their previous high school performance (known as their *ATAR* score), whether they attended a private or government public high school, and their enrolment status (part-time or full-time).
>
> Web usage. The university uses the Moodle Learning Management System (LMS), and we were able to extract data on individual student use of the web-based practice quizzes, as well as data on whether they downloaded certain material during the semester (for example, general feedback on their essay assignment, a document on useful exam hints and techniques, and so on).

The combination of these three data sources means that we had a

TABLE 1

		Completed survey Mean	Did not complete survey Mean	
Student Record Data				
age	Age of student (start of semester)	19.213	19.29	
hs_prev_year	Dummy variable indicating whether the student attended high school in the previous calendar year.	0.634	0.537	***
female_dummy	Gender (1 = female)	0.442	0.344	***
part_time	Whether the student is enrolled part-time.	0.054	0.105	***
ATAR	Student's rank on the high school tertiary entrance examinations	90.339	88.951	**
GPA	Student's Grade Point Average (1-7 scale) at university.	4.939	3.700	***
fail	Given a value of 1 if student ultimately failed the unit (0 otherwise)	0.092	0.381	***
Learning Management System data				
tute	Tutorial mark received by the student for attendance/participation in tutorials during the semester (%).	84.058	59.732	***
quiz_ave	Online practice quizzes attempted (average per topic)	2.323	1.684	***
sa_prac_view	Given a value of 1 if the student downloaded a copy of a pdf document with useful final exam information (0 otherwise).	0.897	0.755	***
essay_feedback_view	Given a value of 1 if the student downloaded a copy of a pdf document with general feedback from the essay assessment (0 otherwise).	0.378	0.316	*
mid_mock_view	Given a value of 1 if the student downloaded a copy of a pdf document of a practice mid semester exam (0 otherwise).	0.870	0.772	***
Survey data				
eng	Whether English is spoken at home	0.779	..	..
deep	Using the revised questionnaire by Briggs (1987), this adds up scores from the questions relating to a deep (motive and strategy) approach to learning. Higher scores indicate a 'deeper' approach.	26.593	..	..
surface	Using the revised questionnaire by Briggs (1987), this adds up scores from the questions relating to a surface (motive and strategy) approach to learning. Higher scores indicate a more 'surface' approach.	25.501	..	..
econs	Whether the student has studied economics prior to this unit (1 = yes)	0.560	..	..
Viewed online lectures:				
lcs_0	Dummy variable with a 1 if the student did not view any of the face-to-face lectures online, or the 'online-only' lecture recordings [omitted variable]	0.154	..	..
lcs_online_only	Dummy variable with a 1 if the student only viewed the 'online-only' lecture recordings	0.149		
lcs_1_25	Dummy variable with a 1 if the student viewed between 1-25% of the face-to-face lectures online	0.295	..	..
lcs_26_50	Dummy variable with a 1 if the student viewed between 26-50% of the face-to-face lectures online	0.124	..	..
lcs_51_75	Dummy variable with a 1 if the student viewed between 51-75% of the face-to-face lectures online	0.124		
lcs_76_100	Dummy variable with a 1 if the student viewed between 76-100% of the face-to-face lectures online	0.154		
LEC	Self-reported lectures attended by student (%)	63.770	..	..
Distance to university:	Natural log of distance to campus (kilometres)	2.145		
public_transport	Dummy variable indicating whether the student travelled to university by public transport (bus or train)	0.550	..	..
work_dummy	Dummy variable indicating whether student was engaged in paid employment during the semester	0.745	..	..
workxworkhours	Interaction term of *work_dummy* with self-reported average hours of paid employment during semester	8.920	..	..

NOTE: Statistically significant differences in means at the 10% (*), 5% (**) and 1% (***) levels.

relatively rich dataset from which to learn about student attitudes and characteristics. Table 1 has some summary statistics for data used in this analysis, including the source of the data for each variable.

It is also worthwhile at this stage discussing the rationale behind the use of the 'deep' versus 'surface' learning variables from the survey. One largely neglected element in the debate on lecture attendance is whether the different learning strategies of students may lead them to prefer one form of content delivery over another. For example, following the methodology of Biggs (1987) and Biggs *et al* (2001), students can be thought of as having either a 'deep' approach to learning or a 'surface' approach. These two learning approaches differ in terms of both the students' motivation and their strategies for learning. For example, it has been noted that students using a more surface approach 'concentrated on surface features of the learning task, such as key words or phrases. Their strategy was to memorize and reproduce elements which seemed appropriate' (Kember *et al*, 1997). Those adopting a 'deep' approach tend to look for the underlying message or theory behind the content, rather than using rote learning techniques. However, it is important to stress this is not necessarily a psychological trait. Students with limited interest in a compulsory unit, for example, may adopt a surface approach to learning in that unit, but use a deep approach in another unit. The question here is not only whether a student using a surface approach performs better (or worse) in terms of their final grade, but whether these different approaches may lead them to attend more (or fewer) lectures.

The questionnaire used in the student survey followed the Biggs *et al* (2001) revised, shorter *Student Process Questionnaire* (SPQ) survey, which consists of twenty questions (rather than the original 42 question survey). Within each of these two factors (deep versus surface) it was possible to distinguish strategy and motive sub-scales. Each of the sub-scales consisted of five items. The final version of the questionnaire therefore has two main scales, Deep Approach and Surface Approach, with four sub-scales: Deep Motive; Deep Strategy; Surface Motive; and Surface Strategy. In this study, we only use the two major factors (Deep Approach and Surface Approach), rather than the individual sub-scales. The answers given by these students are on a five point Likert scale, ranging from 'Always true of me', down through to 'Only rarely true of me'. Answers were then given a numerical score from 1-5, and the scores added up to arrive at the final deep and surface approach scores. In both indicators higher values represent, respectively, a deeper approach to learning, and a more surface approach to learning. The specific questions used in the survey can be found in Biggs *et al* (2001).

Methodology, results and discussion

Sample Selection Bias

Of the 903 students who ultimately received a mark for this unit, 609 participated in the survey. Accounting for those with missing and incomplete data, we were ultimately able to get complete data for 437 of them (48 per cent). Although this is a reasonable sample from our population, as noted above there is still the potential problem that there might be a sample selection bias here. For example, the survey was conducted in tutorials during the final week of semester. Consequently, those who had 'given up', or who were only very tangentially attached to the course were far more likely to be absent from these tutorials. As such, we may have something of a sample selection bias, because the individuals in our sample include only those people who were engaged in this course enough to both come to tutorials and fill out the survey. Omitting those who failed, and who were also more likely not to go to lectures, or view the lectures online, may be problematic, because it will result in biased coefficients if we run the standard OLS regressions.

To get an initial feel for this issue, Table 1 also provides some summary statistics for students who completed the survey, compared with those who did not complete the survey. As expected, there are indeed differences in our two groups. Not surprisingly, the largest difference occurred with respect to those who had failed the unit (of those completing the survey, only 9.2 per cent ultimately failed the unit; however, for those not completing the survey, 38.1 per cent failed the unit). This is also borne out by the tutorial attendance mark (84 per cent for those completing the survey, only 60 per cent for those not completing the survey). Other notable differences include whether the student was enrolled in the course part-time or full-time, whether the student viewed the mid semester mock exam handout and the final exam hints document through the LMS and the student's ATAR (those with higher ATARs were more likely to complete the survey).

We can see therefore, that there are some potentially important differences between the sample used for the econometric study below, and the overall student population for this unit. Ignoring these could lead to spurious conclusions being drawn from these results. Given this, we have used a Heckman two-step regression analysis in order to see whether these biases might affect our results in a substantive way. In Heckman (1976), he assumes there is some underlying relationship:

$$y_j = \beta x_j + u_{1j}$$

However, the dependent variable (y_j) is not always observed. It is observed if:

$z_j \Upsilon + u_{2j} > 0,$
where
$u_1 \sim N(0, \sigma)$
$u_2 \sim N(0, 1)$
$corr(u_1, u_2) = \rho$

If $\rho \neq 0$ (ie the error terms are correlated), then any standard regression run on the first equation will lead to biased results, and a Heckman regression would be appropriate. However, if it turns out that ρ is insignificantly different from zero, then the selection bias is small, and we can proceed with other estimation techniques. Table 2 shows the results of the two-step Heckman regression.

In our analysis here, the first step is to run a probit on the full sample of students, with a 1 if they filled in the survey, and a zero otherwise. The explanatory variables used in this probit are essentially all variables for which we have data for the whole population of students: (1) the tutorial attendance/participation mark for the student; (2) a dummy variable for whether the student ultimately failed the unit; (3) whether they downloaded a copy of practice short answer questions (and answers) prepared for their final exam; (4) whether they downloaded a copy of the document outlining general feedback from their essay assessment; (5) whether they downloaded the ‘mock’ mid semester exam provided for them through the LMS; (6) the age of the student; (7) a gender dummy; (8) whether they were enrolled part-time in the course; and (9) the average number of voluntary quizzes the students attempted during the course of the semester.

The results for this can be seen in the top section of Column 1. As noted above, the main determinants of this were the tutorial mark a student received at the end of the semester (higher attendance equated with a higher probability of doing the survey), whether the student ultimately failed the unit, whether the student was female (more likely to complete survey), and whether the student downloaded the final exam hints document. Therefore, these results show that there is indeed some selection bias in our sample. The more important question though, is whether this makes a substantive difference to our results on lecture attendance.

The second stage involved generating the inverse Mills ratio from the probit model, which is the ratio of the standard normal distribution

TABLE 2

Heckman sample selection regressions

First stage probit (selection variable is the survey dummy variable, where 1 = completed survey, 0 otherwise)	**1**	**2**
Tutorial mark	0.029 0.003 ***	
Failed unit dummy	-0.523 0.130 ***	
Gender (female=1)	0.344 0.100 ***	
Part-time student	-0.140 0.193	
Age of student	-0.003 0.021	
Average practice quizzes attempted	0.010 0.026	
Viewed final exam hint document	0.281 0.143 **	
Viewed essay feedback document	0.037 0.106	
Viewed Mid Semester Mock Exam document	0.142 0.131	
Constant	-2.081 0.481 ***	
Second stage: OLS [Dependent variable = lecture attendance]		
Personal characteristics:		
Age of student	-2.824 1.199 **	-2.851 1.190 **
Gender (female=1)	4.135 2.082 **	4.570 2.039 **
Speaks English at home	1.804 2.755	1.894 2.741
Public transport dummy	4.256 2.441 *	4.246 2.450 *
Distance to university (kms)	-1.834 1.177	-1.903 1.181
Paid employment dummy	6.904 3.499 **	6.949 3.506 **
Paid employment x average hours worked	-0.574 0.202 ***	-0.586 0.203 ***
Academic characteristics:		
Part-time enrolment	-4.244 5.867	-4.234 5.867
ATAR	-0.130 0.164	-0.093 0.154
Prior economics dummy (1=yes)	-2.742 2.085	-2.423 2.085
Attitudes to learning:		
'Deep' learning approach	0.552 0.164 ***	0.587 0.165 ***
'Surface' learning approach	-0.446 0.176 **	-0.454 0.176 ***
Viewed 1-24% of online recordings	1.407 2.591	1.466 2.600
Viewed 25-49% of online recordings	-6.644 3.176 **	-6.756 3.154 **
Viewed 50-74% of online recordings	-19.585 3.449 ***	-19.667 3.456 ***
Viewed 75-100% of online recordings	-18.956 4.031 ***	-19.011 4.015 ***
Inverse mills ratio	-3.922 4.627	
Constant	132.635 30.926 ***	127.365 30.547 ***
P-value on Inverse Mills ratio	0.397	..
Pseudo-R^2 on probit selection regression	0.24	..
R^2 on OLS regression	0.28	0.27
Censored observations	466	466
Uncensored observations	437	437

*Note: both regressions are corrected for heteroscedasticity. *, **, *** signifies significance at the 10, 5 and 1% level respectively* to the standard cumulative distribution, and running it in the second stage OLS regression as an additional explanatory variable (see Greene, 2003, for further details). The greater the statistical significance of this variable in the OLS regression, the greater the bias arising from our original sample selection. (This would not in any case invalidate the results from the OLS, as the inverse Mills ratio is designed to correct for these biases anyway. It merely suggests that these biases are not a substantive problem in the first place.) However, as can be seen in the bottom section of Column 1, even though there were a number of factors that led to a selection bias, these do not make a material difference to the ultimate results from an OLS regression where lecture attendance is the dependent variable. To reinforce this, we re-ran the second stage regression in Column 2, with no selection correction (that is, a standard OLS regression). The results are essentially identical to those in Column 1. In other words, this gives us confidence that these results are 'true' results from this cohort of students, and are not being driven by the fact that some students with certain characteristics are absent from our sample.

Having taken the selection biases into consideration, what then do the results tell us about the determinants of lecture attendance? In terms of the personal characteristics of students, age appears to be a fairly important component of lecture attendance, with younger students attending more lectures. For students who take public transport, it was thought *a priori* that this might be negatively related to lecture attendance, as it takes more effort to come into university, compared with driving a car. However, we found the opposite is true, in that students coming to university by bus and/or train actually attend more lectures (compared with students coming by any other mode of transport). Whilst the time a student must take to come into university does appear to be negatively related to lecture attendance, it is only a marginally significant factor.

Perhaps the most interesting result arising from students' personal circumstances is the paid employment statistics. Compared with those who do not work, those in paid employment actually attend more lectures (6.9 per cent more). However, as can be seen when we interact this with the average number of hours worked, the more a student works, the less they come to lectures. To show this visually, Figure 1 plots the decrease in lecture attendance (compared with those who do not work at all), with 95 per cent confidence intervals being the dashed lines. Up to around 10 hours per week, students attend more lectures than their non-working colleagues. However, after 10 hours per week, it appears as though this starts to have a negative effect on their attendance, again compared with students who do not work. This of course supports the sensible hypothesis that students who work 'too much' in paid employment have less time to focus on their studies. The issue of whether this ultimately affects their academic performance will be briefly addressed in the following section.

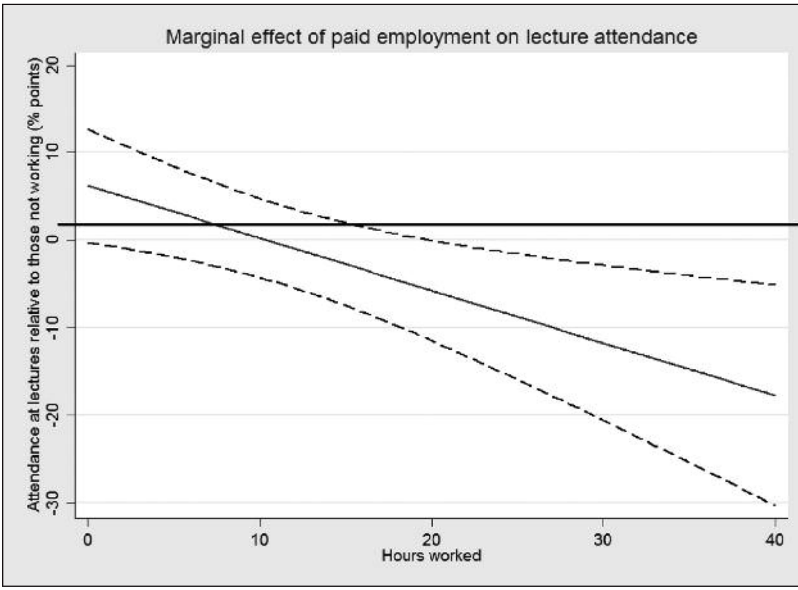

Figure 1. Marginal effect of paid employment on lecture attendance

Turning to students' academic characteristics, it does not seem to matter whether a student is part-time or full-time, or has prior knowledge of economics, in terms of their lecture attendance. The student's ATAR does not appear to have an effect (students with higher ATARs appear to come to marginally fewer lectures, however, this is not significantly different from zero, and is certainly not what we would term a defining characteristic of lecture attendance overall). Lectures are certainly not merely being attended by the 'smart kids'.

Finally, the variables attempting to measure the students' attitude to learning (motivation, effort and so on), brings up some interesting results. In terms of Biggs' 'Deep' versus 'Surface' learners, the evidence here strongly suggests that those who have a deeper approach to learning come to more lectures in person and, conversely, those with a surface approach attend fewer lectures. This should not automatically, however, be construed as being something that harms their ultimate academic performance. ‘Surface’ learning, for example, does not of itself imply laziness, or a lack of effort. What it signifies is that these students try to learn the material through repetition and rote learning, and so the implication here is that surface learners prefer to do their learning through online lectures, whereas deep learners, who are trying to achieve their learning through a more rigorous understanding of the material given to them, have decided the best way to do this is through (initially at least) attending lectures.

With respect to the use of online lecture recordings, the evidence here supports that found in Williams *et al* (2012), in that many students appear to be using the recordings as a substitute for attending lectures, rather than as a complement. Compared with the omitted group (who viewed no online lectures), those viewing less than one-quarter do not show a statistically significant difference in lecture attendance. However, for those viewing over 25 per cent of the lectures online, they attend fewer lectures. For those who viewed more than 50 per cent of the online lectures, they attended roughly 20 per cent fewer lectures.

TABLE 3

P-values of Inverse Mills ratios with selected variables removed from first stage probit regression

Variable removed from first stage probit	**P-value from inverse Mills ratio**
Tutorial mark	0.755
Failed unit dummy	0.214
Female dummy	0.407
Part-time student	0.412
Age of student	0.396
Average practice quizzes attempted	0.408
Viewed final exam hint document	0.462
Viewed essay feedback document	0.397
Viewed Mid Semester Mock Exam document	0.365

Notes: Estimation procedure is the same as Column 1 of Table 2, with one of the selection variables removed at a time. P-values reported here are for the inverse Mills ratio for each regression.

We also subjected our results to a number of sensitivity and robustness tests. For example, Table 3 summarises the p-values from the inverse Mills ratio coefficient when we remove individual selection variables from the initial probit, in order to see whether or not there are specific selection variables that are influencing the results. By and large, the results suggest that there are not.

We also replaced a number of the variables from Table 2 with plausible alternatives, to see whether or not this made any substantive difference to our previous results. Table 4 summarises the results when we (successively) replace age, distance to university, ATAR, and online lecture recording use with plausible alternatives.

Column 1 replaces age with a dummy indicating whether this is the student's first year out of high school. The reason for looking at this is that it may not be the age of the student *per se* that is important, but whether they have only recently come from the more structured world of high school, and are therefore perhaps only coming to lectures because they are used to coming to class in person. This is somewhat borne out by the results, with students coming straight from high school coming on average to 6 per cent more lectures than those for whom this is not their first year out of high school. Both this variable and the variable on age therefore support the view that younger people are more likely to attend lectures.

Column 2 replaces the 'distance to university' variable, with a series of dummy variables taken from the survey that looks not at the distance to university, but at the travel time. Although it is true that students having to travel longer to university come to fewer lectures, in none of these variables is it a significant difference. Therefore, this reinforces the result that distance (or time) is not really a defining feature of lecture attendance for students. Column 3 replaces the ATAR university entrance rank with their university Grade Point Average. Both of these are being used here to control for latent student ability. Whereas we saw no difference in ATAR scores for those attending lectures, using the GPA scores, it does appear as though there is some evidence that students with a higher GPA attend more lectures (significant at the 5 per cent level). Finally, in Column 4 we replace the dummy variables for online lecture usage with dummy variables outlining the students' reasons given for using the online lectures. As one would expect, those who nominate a preference for the online lectures, or who prefer to stay home and watch the lecture, attend far fewer lectures than other students (29 per cent and 17 per cent respectively). Whilst these reflect the preferences of students, others who had to view the online lectures out of necessity (timetable clash or work commitments) also came to fewer lectures (18 per cent and 16 per cent respectively). The final category could be considered as those students who treated online lectures and the face-to-face lectures as complements, rather than as substitutes, and there is no statistical difference in how many lectures they attended.

In conclusion therefore, there are several characteristics that stand out. First of all, those attending lectures tend to be younger and more female (although this is somewhat sensitive to the other variables included). Those with greater work commitments also attend fewer lectures, and this worsens the more hours of paid employment are undertaken. Students attending lectures are also far more likely to be 'deep' learners, with 'surface' learners seemingly favouring viewing the lectures online. Finally, it does appear as though many students treat the lectures and the online recordings as substitutes, rather than as complements.

The results are also interesting for what characteristics *are not* important for lecture attendance. The main one perhaps that is commonly cited is the distance to the university. Although the relationship is certainly a negative one, it is not a statistically significant relationship. Further, it is not necessarily the case that those students with greater abilities come to more lectures. Admittedly, the evidence is more mixed, with it being as insignificant factor when we proxy ability with their ATAR scores, but is marginally significant when we use their university GPA.

Effect of lecture attendance on academic performance

The majority of studies that estimate the determinants of academic performance (for example, Anderson, Benjamin and Fuss (1994), Dobson and Skuja (2005) and Birch and Miller (2007)) are based on an education production function. In this model, a student's tertiary academic performance (AP_i) is a function of a variety of student characteristics. In this model, a large number of characteristics can be controlled for: their personal characteristics (PC_i); their academic characteristics, such as prior academic performance, whether they had prior knowledge of economics from high school, and so on (AC_i), and their attitude to learning, including attendance at lectures ($\mathrm{AL_i}$).

$$AP_i = \mathrm{f}(PC_i, AC_i, AL_i) \qquad (1)$$

It is common for studies to measure students' academic performance by their final mark for their unit of study (usually measured as a mark out

TABLE 4

Alternative variables employed

OLS [Dept variable = lecture attendance]	1		2		3		4	
Personal characteristics:								
Age of student (at start of semester)	..		-2.854	**	-0.349		-4.389	***
	..		*1.189*		*0.609*		*1.245*	
First year out of high school dummy [a]	6.957	***	..		..		..	
	2.656		..		..		..	
Gender (female = 1)	4.071	*	4.598	**	5.113	**	2.749	
	2.080		*2.086*		*2.032*		*2.031*	
English spoken at home	2.475		1.546		1.536		5.594	**
	2.735		*2.721*		*2.534*		*2.713*	
Public transport dummy	4.179	*	4.572		4.838	**	4.086	*
	2.365		*2.823*		*2.266*		*2.309*	
<u>Travel to university:</u>								
10-20 minutes	..		-3.215		..		..	
	..		*4.290*		..		..	
21-30 minutes	..		-4.774		..		..	
	..		*4.347*		..		..	
31-45 minutes	..		-2.892		..		..	
	..		*4.382*		..		..	
46-60 minutes	..		-3.712		..		..	
	..		*4.197*		..		..	
more than 60 minutes	..		-6.356		..		..	
	..		*4.691*		..		..	
Distance to university (kms) [b]	-1.787		..		-1.643		-1.993	*
	1.173		..		*1.063*		*1.062*	
Paid employment dummy	7.598	**	7.013	**	5.737	*	7.443	**
	3.501		*3.525*		*3.327*		*3.266*	
Paid employment x average hours worked	-0.625	***	-0.613	***	-0.521	**	-0.532	***
	0.201		*0.206*		*0.214*		*0.204*	
Academic characteristics:								
Enrolment type (1 = part-time)	-5.625		-3.681		-6.448		-2.740	
	5.677		*5.952*		*5.126*		*5.698*	
ATAR	-0.080		-0.173		..		0.023	
	0.157		*0.164*		..		*0.152*	
Grade Point Average [c]	..		..		1.796		..	
	..		..		*0.823*		..	
Prior economics dummy	-2.817		-2.989		-2.121		-3.473	*
	2.138		*2.100*		*1.975*		*1.938*	
Average practice quizzes attempted	..		..		..		..	
	..		..		..		..	
Attitudes to learning:								
Deep learning approach	0.538	***	0.571	***	0.525	***	0.369	**
	0.165		*0.164*		*0.158*		*0.165*	
Surface learning approach	-0.435	**	-0.467	***	-0.398	**	-0.538	***
	0.178		*0.175*		*0.162*		*0.158*	
Viewed 1-24% of online recordings	1.481		1.128		2.159		..	
	2.588		2.603		2.447		..	
Viewed 25-49% of online recordings	-6.672	**	-6.750	**	-4.855		..	
	3.165		3.090		3.037		..	
Viewed 50-74% of online recordings	-19.346	***	-19.948	***	-18.348	***	..	
	3.417		3.452		3.280		..	
Viewed 75-100% of online recordings	-18.887	***	-19.412	***	-19.994	***	..	
	4.088		4.050		3.737		..	
Viewed online lecture due to timetable clash [d]	..		..		..		-18.927	***
	..		..		..		*6.642*	
Viewed online lectures due to work commitments [d]	..		..		..		-15.786	***
	..		..		..		*4.333*	
Viewed online lectures as I prefer online lectures [d]	..		..		..		-29.741	***
	..		..		..		*3.515*	
Viewed online lectures as I prefer to stay at home [d]	..		..		..		-17.217	***
	..		..		..		*2.880*	
Viewed online lectures for study/revision [d]	..		..		..		-0.298	
	..		..		..		*2.466*	
Inverse mills ratio	-3.749		-3.689		-0.580		-4.344	
	4.634		*4.675*		*4.547*		*4.057*	
Constant	69.989	***	137.000	***	62.978	***	154.852	***
	15.880		*30.850*		*15.969*		*31.081*	
P-value on Inverse Mills ratio	0.419		0.43		0.898		0.285	
R^2 on OLS regression	0.28		0.28		0.27		0.33	
Censored observations	466		437		397		463	
Uncensored observations	437		446		506		440	

*NOTES: First stage probit run, but not shown for brevity. Using robust standard errors. *, **, *** signifies significance at the 10, 5 and 1% level respectively. [a] Age also replaced in probit with 'first year from high school' dummy. [b] Natural log of kilometres. [c] Grade Point Average (1-7). [d] Taken from survey question on reason for using the online lecture recordings.*

of one hundred) and estimate the production function using Ordinary Least Squares (OLS). This procedure allows for the determinants of academic performance to be examined at the conditional mean of university marks. However, there are again potential problems with using that methodology in this paper. For the same rationale as in the section above on lecture attendance, there may be a significant sample selection bias arising from our use of survey data, which ultimately may cause a bias in estimation results using OLS.

The second potential problem with OLS is that it assumes the explanatory variables are exogenous to the dependent variable. This again is unlikely to be the case. Of particular interest here is the relationship between lecture attendance and academic performance. For example, if we find that students who achieve better final grades also attend more lectures, this may be because of the additional benefit they obtain from the lectures. However, it is entirely plausible that students who achieve high scores are more motivated and work harder, which also means they go to more lectures. But it is not the lecture *per se* that gets them the better results, it is the motivation, and hence we have the problem of omitted variable bias. One way to potentially overcome this problem is by finding an appropriate instrument, and running a two-stage least squares regression. A (good) instrument is one that is correlated with the explanatory variable (lecture attendance), but is not a factor for academic performance. So, for example, Stanca (2006) used distance from university as an instrument for lecture attendance, because distance is plausibly associated with how many lectures a student attends, but should be uncorrelated with their grade in the unit. Another possible method is to run the Heckman regression on lecture attendance as above, and then take the predicted values of lecture attendance, and use that in the regression. This at least means that the lecture attendance variable has already taken into account the variety of factors that influence lecture attendance directly. In the analysis that follows we use both approaches.

Table 5 reports the results with the student's final mark in this unit as the dependent variable. Many of the explanatory variables are similar to those used above, with the inclusion of one additional variable to try to capture 'effort', which is the number of voluntary practice quizzes the student attempted over the course of the semester, as well as a dummy variable that indicates whether or not the student attended a government-run public high school. Column 1 runs a simple OLS estimation, with no correction for sample selection. Here, we see a large number of factors that have a statistically significant effect on academic performance, including age (older students on average do better), gender (female students on average earn 6 percentage points lower marks than their male colleagues), paid employment, a student's ATAR, whether they have prior knowledge of economics (which translates into a 5 percentage point higher mark); effort (greater effort proxied through more practice quizzes), a deep approach to learning (results in higher marks), surface learning (results in lower marks), and viewing more than 25 per cent the lectures online (with this effect rising the more lectures are viewed online). Interestingly, for the employment coefficient, these results suggest the opposite to that found for lecture attendance. Those who work any amount have a lower mark by around 5.7 percentage points; however, more hours worked translates into higher marks.

Finally, lecture attendance itself appears to have a large and positive effect on academic performance.

This estimation, however, may still suffer from the same potential sample selection problem as the previous analysis. Using the same probit model as above, we incorporate the inverse Mills ratio into the regression (Column 2). In contrast to our lecture attendance regressions, we find that now the sample selection bias is quite large. In Column 2, with the inverse Mills ratio included, the coefficient has a t-statistic of 5.48, and is therefore significant at the 1 per cent level. Does this make a difference to the results seen in Column 1? For many variables, it does. Employment (and its interaction with hours worked), as well as deep and surface learning approaches, are no longer significant at any conventional level. For others, the coefficients obtained in Column 1 are reduced substantially. For our purposes here, the main one of interest is in terms of lecture attendance, where the coefficient almost halves (from 1.05 down to 0.58). It is, nevertheless, still a highly significant determinant of academic performance. To put that into some context, the coefficient here suggests that for every one percentage point increase in lecture attendance, final marks increase by 0.58 per cent. For a student attending the mean number of lectures (64 per cent), an increase in attendance to 100 per cent would result in a mark that is around 20 percentage points higher. The effect of online lectures viewed also decreases. For those viewing between one-quarter and one-half of lectures, this no longer has a positive and significant effect on academic performance. For those viewing more than 50 per cent of the lectures online, the coefficients are considerably smaller, but are nonetheless still significant determinants of academic performance.

As a test to see how robust our results are to the specification we have employed here, in Column 3 we run a two-stage least squares regressions. As noted above, one way potentially to overcome the endogeneity issue is by finding an appropriate instrument (or instruments), and running a two-stage least squares regression. A good instrument is one that is correlated with the explanatory variable (lecture attendance), but is not a factor for academic performance. In terms of our analysis here, in (2) below academic performance (AP_i) is a function of lecture attendance (LEC_i), and a range of other explanatory variables (X_i).

$$AP_i = \beta_o + \beta_1 LEC_i + \beta_i X_i + \mu \qquad (2)$$

The variables in X_i are:

X_i = (*age, female, part_time, eng, work, work x workhours, ATAR, econs_dummy, govt, quiz_ave, deep, surface, 1-24 per cent, 25-49 per cent, 50-74 per cent, 75-100 per cent)* (please see Table 1 for a description of each).

If LEC_i is correlated with the error term in equation (2) above (μ) then we require an instrument (z_i) for this, so that cov(z_i, μ) = 0. In this analysis, we use a number of instruments for lecture attendance. In the first stage of the regression, we regress these on LEC_i:

$$LEC_i = \beta_o + \beta_1(car_i) + \beta_2(timetable_i) + \beta_2(distance_i) + X_\mathrm{i} + e \quad (3)$$

Where:
car_i = a dummy on whether the student has a car;
$timetable_i$ = whether the student has nominated ‘timetable clash’ as the reason for viewing online lectures and not attending lectures;
$distance_i$ = the natural log of distance from the student’s nominated address (postcode) to the university campus;

A car ownership dummy has been used because in theory whether one has a car or not should be immaterial to academic performance, but may again affect the student’s ability to attend lectures. There is also no reason *a priori* why a timetable clash would result in a lower grade, unless it was due to missing the actual lecture. Finally, the distance (in log kilometres) was used because how far away the student is from university may influence how many lectures they attend, but not their final grade. In the second stage of the regression, we take the predicted value of lecture attendance and run this in place of LEC_i regression (1) above.

The results from this 2SLS can be found in Column 3. Of most interest is the lecture attendance variable and, although the coefficient is

TABLE 5

Regression analysis with final marks as the dependent variable

Dependent variable: Final mark in unit (%)	1	2	3
	Uncorrected	With sample correction	IV (2nd stage)
Age of student (at start of semester)	4.549 *0.785* ***	3.112 *0.754* ***	2.540 *1.090* **
Gender (female = 1)	-5.985 *1.341* ***	-4.985 *1.278* ***	-3.283 *1.653* **
English spoken at home	-3.781 *1.343* ***	-3.733 *1.280* ***	-3.002 *1.900*
Paid employment dummy	-5.725 *1.900* ***	-2.324 *1.842*	-1.213 *2.801*
Paid employment x average hours worked	0.335 *0.139* **	0.070 *0.134*	-0.025 *0.209*
Enrolment type (1 = part-time)	4.524 *2.670* *	2.420 *2.617*	2.290 *4.175*
ATAR [c]	1.221 *0.079* ***	1.077 *0.078* ***	1.158 *0.126* ***
Prior economics dummy	5.211 *1.060* ***	2.975 *1.017* ***	4.035 *1.506* ***
Attended government-funded high school	0.446 *1.057*	0.464 *1.010*	1.309 *1.522*
Average practice quizzes attempted	1.035 *0.227* ***	0.843 *0.218* ***	0.978 *0.312* ***
Deep learning approach	-0.287 *0.132* **	-0.094 *0.129*	0.036 *0.194*
Surface learning approach	0.228 *0.125* *	0.019 *0.120*	-0.068 *0.168*
Viewed 1-24% of online recordings	-0.547 *1.133*	-0.332 *1.100*	0.254 *1.479*
Viewed 25-49% of online recordings	5.672 *1.947* ***	2.631 *1.883*	1.524 *2.692*
Viewed 50-74% of online recordings	21.854 *3.953* ***	12.589 *3.956* ***	10.138 *5.418* *
Viewed 75-100% of online recordings	23.025 *3.958* ***	13.997 *3.849* ***	12.114 *5.344* **
Lectures attended	1.053 *0.182* ***	0.579 *0.181* ***	0.470 *0.236* **
Inverse Mills ratio	.. ..	-11.518 *2.103* ***	.. ..
Constant	-201.486 *27.216* ***	-122.461 *28.068* ***	-120.063 *37.639* ***
P-value on inverse mills ratio	..	0	..
F-test on instruments	..	..	2.12823
P-value on F-test	..	..	0.0961
Overidentification test (p-value)	..	..	0.2648
R^2	0.56	0.59	
Obs	429	429	426

*Note: Column 3 is a 2SLS regression, with lectures attended being instrumented by: (1) whether the student used a car to get to university; (2) the log of distance to university, and (3) whether the student nominated 'timetable clash' as reason for missing lectures. Second stage only reported. Using robust standard errors. *, **, *** signifies significance at the 10, 5 and 1% level respectively.*

slightly lower than in Column 2, it is nevertheless still a significant determinant of a student's final grade. The sign and magnitude of most of the other variables are also very similar to the results found in Column 2. However, one problem we have with this is that the instruments turn out to be relatively weak. As a general rule of thumb, an F-test value of at least 10 is a sign of good instruments. Here the F-test is only 2.1, which is well below this threshold. Therefore, although the results from the instrumental variables estimation support the findings using the sample-correction model, the fact that the instruments are quite weak means we perhaps should not put too much emphasis on this result.

In terms of the relationship between a student's attitude to learning, their attendance at lectures, and their academic performance, a couple of points are worth noting. First of all, the 'effort' variable, (proxied through the student use of voluntary practice quizzes) is a highly significant determinant of overall academic performance. The student's learning approach was extremely important in terms of whether they attended lectures or not, but in Columns 2 and 3, not significant determinants at all of overall academic performance. In other words, to the extent that students have a deep or surface approach to learning, the main area this impacts on is through lecture attendance, which then has an impact on academic performance. It is, of course, quite possible that this is mainly because it is an introductory unit, and so students can still attain good grades through the surface approach of rote learning. It would be interesting to see whether this remains true at later stages of a student's course, but this is outside the scope of this paper.

Concluding comments

In summary therefore, the evidence presented here does suggest that attending lectures does have some benefit for students. Importantly, we have tried to take into consideration two statistical problems that have plagued a number of previous analyses in this area: the fact that lecture attendance is endogenous to academic performance, and the problems associated with relying on survey data. When addressing the issue of the characteristics of students attending lectures, the first point to note is that there is essentially very little sample selection bias, and certainly none that appears to heavily influence the results. These results by and large confirm what others have shown previously, in that attendance is negatively affected by work, and timetable clashes. Younger students and females are more likely to go to lectures. An interesting result that has not to our knowledge been explored previously relates to the important role that students' attitudes to learning have on lecture attendance. Those who have a deeper approach to learning are more likely to go to lectures, whilst those favouring a surface approach attend fewer lectures.

With respect to the determinants of academic performance, many of the results again confirm previous research, such as those relating to ability (Birch and Miller, 2007), and prior knowledge of economics (Williams *et al*, 2012). In terms of this analysis it is interesting that, even after controlling for a variety of factors that affect student performance, attendance at lectures was (statistically) a consistently important factor. The fact that it is still a statistically significant determinant of academic performance, even after controlling for issues such as effort and attitudes to learning, gives us some confidence that we are indeed capturing the benefit of the lecture itself, rather than these other proximate causes.

Despite these results, there is still a lot that remains unanswered. If, as suggested here, attending lectures does provide benefit to students, it is not clear from our research precisely what that benefit may be. This would, of course, require a different type of analysis to that undertaken here. Nor are we saying that attending lectures is necessarily 'better' than viewing them online. As we saw in Table 5, there was also a positive association between viewing the majority of the lectures online and academic performance as well. Rather, this paper should be viewed as an attempt to show that both have value, even after 'netting out' issues such as motivation and effort. Perhaps a potentially more important aspect of this research is to further our insights into the characteristics of students who attend lectures, particularly with respect to their attitudes to learning ('deep' versus 'surface'). Finally, it is also important to stress that these results relate to a particular cohort at a particular point in time. Consequently, we view these results as suggestive, rather than definitive, and future research that applies this model to different cohorts over time may help to confirm (or otherwise) these results.

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