A study of the effects of online lecture viewing on class attendance, academic achievement and the productivity of study

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Abstract: We study how online lecture viewing technology affects student lecture attendance, academic achievement and the productivity of study in a large first year economics course in an Australian university. We do this by collating data on the students' use of lecture recordings including frequency and timing, their study hours, their final achievement measured as marks, as well as a number of demographic variables. We supplement this with data on focus group interviews. We find some evidence that students substitute between attending lecture and viewing lectures online. The viewing of lecture recordings has a positive impact on achievement depending on when the viewing occurs. If lecture recordings are viewed contemporaneously with the lectures on a regular basis, the effect on achievement is positive. But if lectures are viewed later, such as at the end of the semester as an exam study tool, the effect on achievement is not statistically significant. We also find evidence that viewing lecture recordings is a relatively unproductive use of study time in terms of the effect on final student marks.

Keywords: recorded lectures, class attendance, student achievement.

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1. Introduction

Universities around the world are grappling with the question of how to deploy new teaching and learning technologies in a way that meets student demand for convenience and a better learning experience, while also achieving good learning outcomes. MOOCs[1] are perhaps the most significant and rapidly growing example. This paper focusses on another technology, Lecture Capture and Streaming Technology (LCST), which enables students to view lectures online by accessing the sound and screen content exactly as it was presented in the lecture. A concern among teaching academics is that student attendance in lectures will fall and that this will adversely affect learning outcomes (Massingham and Herrington 2006, Chang 2007). Yet some studies claim that the availability of online lecture viewing and podcasts have no effect on lecture attendance (Copley 2007, Larkin 2010).

When offered a new learning technology, students will make choices about how to use it according to their preferences for academic achievement, leisure time and alternative ways of learning for a given expected effect on achievement (Guest, 2005). Hence it is not at all clear that learning outcomes as reflected in academic achievement will necessarily improve. Technology such as LCST provide students with a virtual lecture experience without physically attending, which provides valuable flexibility in time allocation which allows, for example, students to take more paid work hours or care for children. It also provides students for whom English is a second language with a tool to overcome language issues that may arise in the lecture, and allows students who live a long way from campus to avoid a long commute time.

This paper examines how LCST affects class attendance, academic achievement and the productivity of study time. We do this by collecting data on both the use of LCST as well as hours spent studying by students participating in a large first-year economics course. We supplement this with data on focus group interviews.

The paper is structured as follows. Section 2 discusses the use of LCST and its potential effects on attendance, achievement and study time productivity. Section 3 discusses the survey instruments and provides descriptive statistics of the data. Section 4 reports the results, while Section 5 discusses and concludes.

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[1] Massive Open Online Courses.

2. Lecture capture technology, attendance, learning outcomes and study time productivity.

Recently, many universities have acquired the technology to record lectures and make them available for online viewing to students, which we dub Lecture Capture and Streaming Technology (LCST). Furthermore, a growing number of universities have made its use compulsory *en masse* across all courses (Bailey and Houghton, 2011). This move has sparked a fierce debate in the tertiary education literature. There are two central concerns at play in this debate. Firstly, what does this technology mean for the future of lectures? Secondly, what will it mean for learning outcomes?

2.1 Effect on lecture attendance

Given the availability of recorded lectures that can be viewed any time on their home and portable computers, students may be less willing to accept the costs associated with attending lectures on campus, such as work commitments and travel interruptions (Chang, 2007). This will be particularly the case where, because of the nature of the learning activities occurring in the lecture, viewing lectures online is seen as a close substitute to attending the live lecture. Attendance costs are also higher for students who have more paid work commitments and/or a further distance to travel to campus. Any effect however must be separated from the long term downward trend in student attendance that pre-dates the introductions of LCSTs (Massingham and Herrington 2006). This trend is thought to reflect more fundamental changes in student lifestyle patterns, including a greater tendency to engage in part time work whilst studying. In one report, for example, 71% of Australian university students were found to undertake paid employment during semester, working an average of 15 hours per week (Australian Vice-Chancellors' Committee, 2007).

In this respect, it is interesting that some studies have found little evidence that the introduction of LCST actually affects lecture attendance. Larkin (2008) interviewed 68 students at the beginning and end of a course and found that the presence of LCSTs had no influence on self-reported lecture attendance. Similarly, Copley (2007) questioned students about how LCSTs affects lecture attendance and found only 12 per cent of students indicated that this technology would negatively affect their lecture attendance. On the other hand, in a considerably larger survey of 815 students across various universities, Gosper (2008) found that over 56 per cent of student reported that they attend lectures less frequently due to LCSTs. A chief drawback of these studies is that lecture attendance was not directly observed, but rather reported by students to the researcher. Indeed von Kronsky et al. (2009) analyzed actual attendance records and found evidence that a small percentage of students watched lectures exclusively online rather than attending the class, while others used the LCST to catch-up the occasional missed lectures. On the whole however, the latter tendency was small and the authors concluded that lecture attendance was not affected by the introduction of LCST.

2.2 Effect on learning outcomes.

The second question is how LCST affects learning outcomes. In this regard, LCSTs are seen to have both positive and negative effect on learning outcomes. On the one hand, if used as a supplement to lectures, LCSTs reduce the need for students to write notes in lectures and enable them to potentially focus on deeper engagement with the material. LCSTs may also help students review parts of the lecture that they had difficulty in understanding, and reduce the student's dependence on their own recorded lecture notes during subsequent revision. On the other hand, LCSTs may also reduce student-faculty interaction, reduce the ability to immediately ask questions about the material, and provide them with the potential to defer work and engage in 'binge' studying close to exams (Figilo, 2010). Hence the effect of LCSTs on learning outcomes may dependent on the timing of its use – that is, the degree to which it is used reasonably contemporaneously with the lecture to fill in gaps in understanding, compared with its subsequent use, prior to exams for example.

It is therefore perhaps not surprising to find that empirical studies have yielded mixed results about the effects of LCSTs on learning outcomes (von Konsky et al 2009). In a study of an undergraduate Engineering class, McCredden and Baldock (2009) found that students who used LCSTs tended to perform academically worse than other students. These students reported problems with the lecture in terms of seeing the blackboard, understanding the lecturer and the difficulty of the material. A negative effect on learning outcomes has also been confirmed amongst particular types of students by Figilio et al (2010) who report on the effects of 'live' versus 'online' lectures on learning outcomes in a large first-year economics course in the US. The results show that the overall effect of live instruction relative to online instruction on learning outcomes is not statistically significant. However, this average effect masks substantial differences that occur between different subgroups of students. In particular, students with a record of poor academic achievement (measured via high school performance and university GPA) tended to perform significantly worse in their assessment when they watched lecture ‘online’ rather than ‘live’. A similar effect was found amongst male students. In addition students from multicultural backgrounds, such as Hispanic students, also tended to perform worse when listening to the lecture ‘online’ rather than ‘live’. No significant differences were found amongst female students, white students, black students, or high achieving students.

2.3 Study time productivity

What students do with their out-of-class study time may be at least as important as how many hours they spend on it. Biggs (1999) talks about active and passive learners. Active learners are curious, searching for meaning, unlike passive learners who are interested only in remembering enough to pass. Academic teachers can encourage active learning by designing appropriate learning environment including resources and activities. Biggs notes that the historical tendency for universities to cater toward elite students has led to the emergence of a particular teaching format (a combination of lectures and tutorials) that is characterized by passive student engagement which works better for high ability students. He goes on to argue that the more diverse student body in terms of ability, culture and other factors implies a need for more active student engagement: “Good teaching is getting most students to use the higher cognitive level processes that the more academic students use spontaneously”(Biggs, 1989, p.4).

The question for our purposes is whether the use of LCST encourages active learning. Viewing recorded lectures may be a relatively passive learning activity compared with redoing tutorial questions and problems. It is hard to be definitive about this, since it depends on the nature of the lecture material and what students do with it. But there may well be a temptation to simply look at a screen. If students use LCST passively, then LCST may contribute to a relatively unproductive use of study time.

Our study is not able to determine exactly what students do with recorded lectures through LCST. But we do have data on students’ total study time, their use of LCST and their final achievement level. This allows us to determine whether the use of LCST in students’ private study time is positive for achievement. That is, it allows us to determine whether LCST is a relatively productive use of study time.

3. Method and Data

At the start of semester, we conducted an in-class survey during the first lecture of the course which collected the following data:

i. Demographic data: age, gender and student number, and whether English is a second language
ii. Time constraints on study: commuting time to university, hours worked
iii. Accumulated study: OP score, number of subjects previously studied.

The number of students who completed the survey was 229 and the total number of students enrolled in the class was 420. The response rate to each question is reported in Table 1 below, and the descriptive statistics are given in Table 2. To assess the representativeness of this sample, we examined how the distribution of final grades received by students in this sample compared to the distribution of final grades in the total population of students. We found that these compare well to the overall student population and it suggests there is no major bias in the survey against or in favour of high achieving students. In addition to the survey data, we tracked lecture attendance for a sample of 5 out of a total of 11 lectures during the semester (see "Lecture Attendance" in Table 2). Appendix 1 reports the correlation matrix across all variables.

INSERT TABLE 1 AND TABLE 2 ABOUT HERE

In addition, data from the Lecture Capture System (LCS) gave us information on the date on which a lecture capture file was accessed by students as well as the date of the lecture recording. This provides enough information to calculate the lag in terms of the number of days between the lecture recording and the date of access by students. We can therefore examine the use of lecture capture on two levels. First, we examine the influence of the total number of times ("hits") the student has accessed lecture capture files in order to study how such usage influences learning outcomes. In addition, we examine whether the overall effect of LCS usage on learning outcomes is different in terms of the timing of the use of lecture capture. Hence we create two variables (reported in table below): i) contemporaneous use (*LC_Cont*) which is defined as the number of hits on lecture capture files within two weeks of the lecture; ii) subsequent use (*LC_Sub*) – hits on lecture capture files more than two weeks after the lecture.

FIGURE 2 ABOUT HERE

The final source of data was the weekly online diaries which students completed each week during the semesters. As an incentive to participate, students who completed the diary were placed in a lottery to win bookshop vouchers. The diary recorded the average number of hours per week dedicated to studying 1303AFE. The question posed was “Apart from attending lectures and tutorials, how much time did you spend studying 1303 AFE at home in the past week?” This question was administered online and appeared when students accessed lecture capture files. These answers were summed across 9 study weeks. Table 3 provides the summary statistics for these variables and shows that the average total number of study hours per students was 17.27, which represents approximately 2 hours of study at home per week. Students not participating in the study had the option of accessing the file without answering the survey.

TABLE 3 ABOUT HERE

4. Results

4.1 The effect on lecture attendance

While we do not have a control group and therefore cannot observe study patterns in the absence of lecture capture, we can examine evidence for a substitution effect between the intensity of LCST use and lecture attendance among students. Intensity of LCST use is defined as the number of times that the student has accessed lecture capture files in the semester. The attendance variable is only a rough proxy for actual student attendance, as the presence of students in the lecture was surveyed in 5 out of the 12 lectures.

FIGURE 3 ABOUT HERE

Figure 2 presents a simple scatter plot of attendance (vertical axis) versus lecture capture use measured by number of hits (horizontal axis). It shows a negative correlation of -0.1123 which is statistically significant at 15 per cent (according to an ANOVA test). This suggests, albeit weakly, that students substitute between attending lecture and using lecture capture.

4.2 Learning outcomes/achievement

Learning outcomes are measured by the level of academic achievement, defined as the final grade for the course which includes the student’s performance in the mid-semester exam (45 per cent), tutorial exercises (10 per cent) and final exam (45 per cent). We examine the factors that explain a student's grade, which includes their use of lecture capture and the number of hours they spent studying at home, among other variables. The following regression model is estimated:

$$g_i = \beta_0 + \beta_1 LA_i + \beta_2 LC_i + \beta_3 study_i + \beta_6 time_i + \beta_5 dem_i + \epsilon \quad (1)$$

where g_i is the grade (mark) attained by student i; LA is the number of lectures attended; LC is the total number of times lecture capture files have been accessed in the semester; *study* is the number hours studied at home; *time* is a vector of variables that represent time constraints on study performance, consisting of weekly hours in paid employment and commuting time to university; and *dem* represents the vector of demographic characteristics consisting of age, gender, whether English is a second language, whether the student is a domestic or international student, university entry score, and whether parents also have a university degree. While we expected considerable overlap in the demographic variables, the correlation matrix (Appendix 1) reveals a surprisingly low correlation among them.

We are mindful of the possibility of endogeneity in this regression, given the possibility that high achieving students may be more likely to engage with learning resources more frequently including the LCST. Endogeneity would imply that LCST usage (the *LC* variable) is co-determined by grades. To examine this possibility, we compare a simple OLS model with a two stage least squares (2SLS) model in which lecture capture usage is instrumented with the square of lecture usage (LC2). In addition we deal with the constraint that the value dependent variable is limited to the range between 0 and 100. This suggests the appropriate econometric approach would be to use a censored model. For this reason we use a censored Tobit, with a defined upper limit of 100 and defined lower limit of 0. Table 4 below compares the basic OLS model with the 2SLS and the censored Tobit model.

TABLE 4 ABOUT HERE

The results show that lecture capture 'hits' (*LC*), the number of lectures (*LA*), and hours studied at home (*study*) all have a positive and significant effect on learning outcomes. Concerning the demographic variables, it is interesting to note that *age* has a negative and relatively significant impact on learning outcomes. An inspection of the age distribution reveals that there were very few mature age learners in the sample, which means that the results tend to reflect differences between first, second and third year undergraduate students. A possible explanation for the negative *age* coefficient is that students who are taking an introductory economics degree in their final year of study tend to do so in order to complete certain degree requirements; these students may be less motivated than first year students who are embarking on a Commerce degree, for whom introductory economics is a core requirement.

Variables that were found to have no significant influence on learning outcomes at the α=10 per cent level include study load, as well as the number of previous subjects studied, the dummy for non-native English speakers, commuting time to university, the dummy for prior degree, hours worked. All of these variables except for study load were kept in the regression as it was found that their omission reduced the goodness of fit of the model.

We now examine whether the impact of ICST use on learning outcomes is dependent on the timeframe in which this resource is used. We do so by comparing ‘contemporaneous’ versus ‘subsequent’ use of the ICSTs, reported in Table 5. If access to the data has been within 14 days of the lecture date, it is classified as a ‘contemporaneous’ viewing. If it has taken place more than 14 days after the lecture, it is classified as a subsequent viewing.[2] The following model is estimated as Tobit regression:

$$g_i = \beta_0 + \beta_1 LA_i + \beta_2 LC\_sub_i + \beta_3 LC\_cont_i + \beta_4 study_i + \beta_5 time_i + \beta_6 dem_i + \epsilon \qquad (2)$$

The most striking results of the model in Table 5 is that it appears that only ‘contemporaneous’ use of lecture capture (*LC_cont*) has a positive and significant impact on learning outcomes, while *LC_sub* has no significant impact on learning outcomes. This suggests that the effect of LCSTs on learning outcomes depends on the timing of usage which in turn may indicate the purpose of LCST usage. Subsequent use of LCST may reflect binge studying prior to the exam, while contemporaneous use may reflect a desire to improve understanding – a deeper approach to learning perhaps. If so, it is not surprising that contemporaneous use has a positive effect on achievement while subsequent use does not. Given that LCSTs provide more flexibility to students in terms of when to study, it is worth examining in future studies whether the presence of LCSTs in fact changes student studying patterns by giving them a greater incentive to delay study until the end of the semester.

TABLE 5 ABOUT HERE

[2] For the sake of robustness we have checked the following results by varying the selection of 14 by adding and subtracting two days – results were found to be robust.

4.3 Study time productivity

The question here is whether the use of LCTS is a productive use of a student's out-of-class study time. The productivity of out-of-class study time is defined as the incremental (marginal) contribution of each hour of out-of-class study time to the student's final mark. The answer depends on how students engage with the recorded material compared with how they engage with other material during their out-of-class study time. We cannot observe what students do when they are viewing the material. However we can use the data on total study time and usage of LCST to indicate the effectiveness of study time allocated to LCST usage. We do this by modifying regression (2) to include an interaction term (*LC-study*) which is study time outside of class multiplied by the total number of lecture capture hits (excluding repeats) – reported as model *G* in Table 6).

The coefficient on the interaction term is negative and significant at 10 per cent, indicating that higher LCSTs usage is associated with a negative productivity shock to study time. This suggests that, for a given study time, greater usage of LCST lowers achievement. Hence, viewing lecture recordings is a relatively unproductive use of study time even though the separate effect of LC usage is positive for achievement. That is, for a given amount of study time, LCST is positive for achievement; and similarly for a given LCST usage, study time is positive for achievement. But allocation of study time to LCST usage is a relatively unproductive use of study time. This is a subtle yet important finding about the usage of LCST.

To investigate this effect further, we then separate LC usage into the two components, contemporaneous hits and subsequent hits, in models *H* and *I* respectively. This is done by interacting study time with contemporaneous LCST use (*LC_cont-study*) in model *H* and subsequent use of lecture capture (*LC_sub-study*) in model *I*. The coefficient on *LC_cont-study* is negative, relatively large and significant at 6 per cent but the coefficient on *LC_sub-study* is smaller and only significant at 15 per cent. This indicates that contemporaneous LCST usage is more strongly associated with unproductive use of study time than is subsequent usage of LCST.

Some support for these findings is evident in model *J* where we replace total 'study time' with two disaggregated measured of hours dedicated to regular study hours that take place during the semester (*regular study hours*) and study hours dedicated to revising for the exam that take place just before the exam (*revision study hours*). The latter is simply defined as the number hours of study undertaken in the week before the mid-semester exam.[3] As shown in Table 6, model *J* supports the important role that *regular study hours* seem to have on learning outcomes since the coefficient on this variable is large and significant at 1 per cent. The coefficient on *revision study hours* is much smaller and not significant. These results are consistent with the finding in Model *A* (in Table 5) that non-contemporaneous use of LCST has no significant effect on learning outcomes.

5. Conclusion

There is little doubt that the flexibility of blended learning technologies improves the student experience. But whether they improve learning outcomes is another matter and one which naturally concerns educators. This paper is concerned with lecture capture technology that allows students to view and hear recorded lectures including any visual learning resources that can be digitally captured. The results of the analysis are threefold. First, the number of "hits" on LCST is negatively correlated with class attendance. That is, there is some substitution between class attendance and LCST usage. Second, student use of LCST has a positive impact on achievement only if the lecture recordings are viewed contemporaneously with the lectures (defined as within two weeks of the lecture). There is no positive impact on achievement if lectures are viewed non-contemporaneously, such as at the end of the semester for the purpose of exam revision. Third, the viewing of lecture recordings is a relatively unproductive use of study time in that a given amount of study time allocated to LCST is associated with lower achievement.

The main limitation of this study is the absence of a control group and a treatment group. There were ethical reasons for this. Establishing a control group within the cohort of students enrolled in the course and preventing them from accessing the lecture capture technology was not ethically defensible. Instead, all students had access to the technology but we were able to construct a variable that measured the intensity and timing of use of the technology. Subject to this limitation, the results are both encouraging and troublesome: encouraging in that the use of lecture capture contemporaneously with the lecture was positively associated with achievement; but troublesome in that viewing lecture recordings may not be the most productive use of study time. It may encourage a passive approach to study time. This may say as much about the lecture that is being viewed as it does about the

[3] Because the online diary ended before the final exam, we do not have data about the number of hours studied before the final exam.

technology. However it is a reminder of the need to consider the effects of blended learning technologies on learning outcomes as well as the student experience.

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Table 1. Response Rate to student survey.

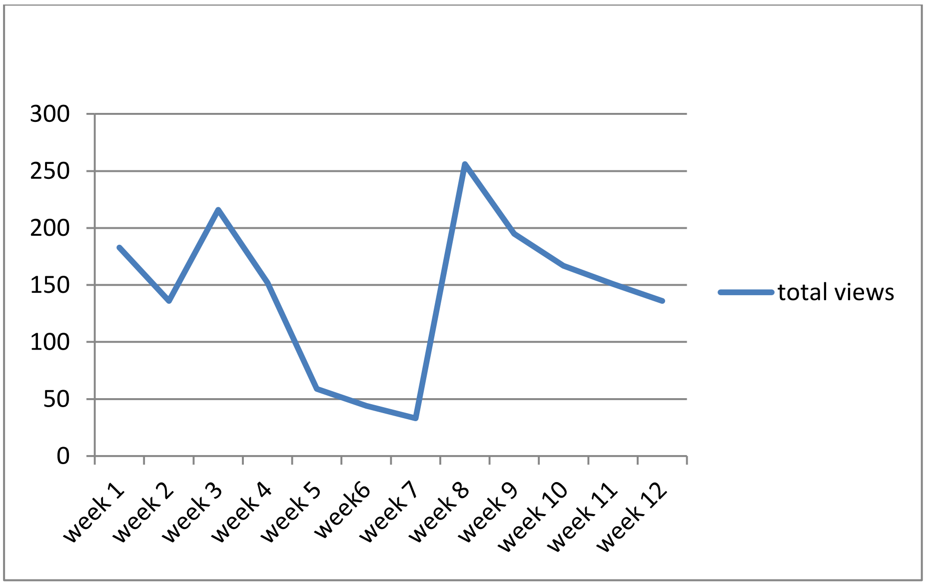
	Question	response
Q2	Your gender is?	56%
Q3	Your age is?	50%
Q4	Is English your second language?	55%
Q6	How many subjects have you completed at University?	54%
Q7	How many subjects are you studying this semester?	56%
Q8	Did either of your parents graduate from University?	56%
Q9	What was your OP rank to gain entry into University?	44%
Q10	How many hours do you work per week?	54%
Q11	Do you have a prior degree from University?	56%
Q12	How many minutes does it take to get to University?	56%

Table 2. Descriptive statistics of variables from student survey and lecture role.

Variable	Obs	Mean	Std. Dev.	Min	Max
Grade Range 0-100	389	65.60	18.94	0	96.25
Lecture attendance Range 0-5	389	1.67	1.78	0	5
Gender dummy 1=male, 0 =female)	214	0.5	0.50	0	1
Age	193	20.75	6.04	0	53
ESL dummy (1=yes, 0=no)	215	.18	.38	0	1
Domestic dummy (1=yes, 0=no)	211	0.83	.37	0	1
Previous subject	206	3.15	5.28	0	30
studyload	217	3.89	.75	0	6
Parents completed uni	216	0.29	.45	0	1
Op	128	10.52	3.50	2	18

Censored between 1-24					
Hour worked	198	14.39	11.21	0	50
Prior degree dummy	216	0.04	0.20	0	1
Commute time (reported in minutes)	217	28.38	19.22	1	120

Figure 1: Total views of lecture capture files across the semester.



Note: sourced from lecture capture usage data. It should be noted that there was a two week teaching break between week 5 and 6 due to a public holiday and mid-semester break. This may have contributed to the unusually low viewing figures in weeks 5 and 6 due to many students either going on holliday or concentrating on other studies. The midsemester exam was scheduled at the end of week 8

Table 3 Descriptive statistics of variables from LCS data and weekly diary.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Total LC views	388	4.86	9.84	0	88
LC-Cont	388	2.45	4.91	0	45
LC-Sub	388	2.40	6.00	0	62
Total Study hours	389	17.26	8.24	0	42
contemporaneous hours	389	16.66	7.98	0	45
subsequent hours	389	1.71	1.34	0	5

Figure 2: scatterplot of attendance versus lecture capture use.

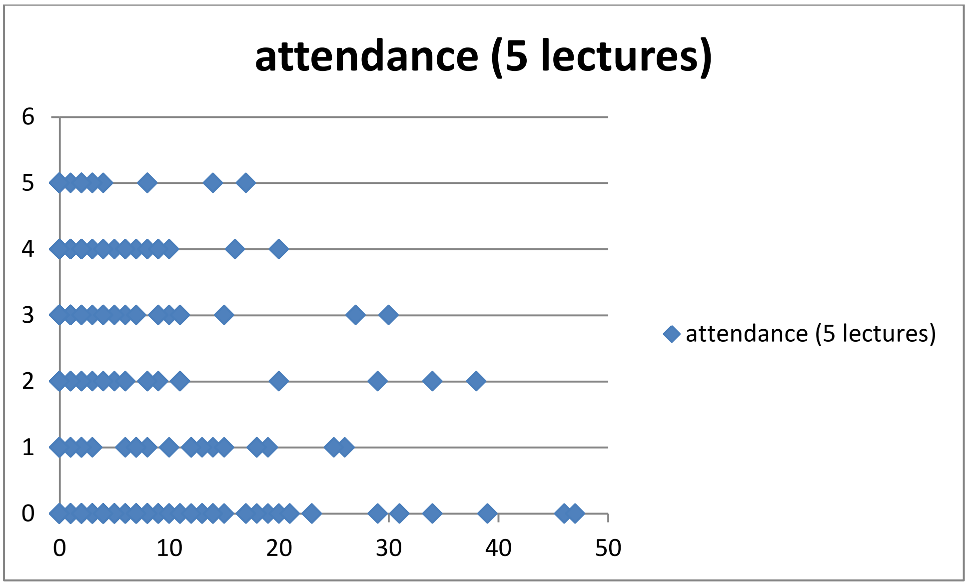


Table 4: Determinants of overall grade: Comparison of OLS, 2SLS and Censored Tobit results.

variable	OLS	2SLS	Tobit
LA	2.404	2.343	2.517
Std. error	1.056	0.979	1.007
P-value	0.025	0.017	0.014
LC	0.866	0.754	0.903
Std. error	0.246	0.331	0.318
P-value	0.011	0.023	0.006
study	0.558	0.575	0.583
Std. error	0.249	0.231	0.238
P-value	0.028	0.013	0.016
Demographic variables			
Age	—2.800	—2.764	—3.008
Std. error	4.054	0.776	0.810
P-value	0.092	0.000	0.000
Subject studied	0.175	0.172	0 .216
Std. error	0.481	0..445	0.458
P-value	0.716	0.700	0.638
OP	0.862	0.846	0.936
Std. error	4.055	0.482	0.497
P-value	0.101	0.079	0.063
Dummy – Gender	—5.313	—5.328	—5.646
Std. error	3.675	3.402	3.502
P-value	0.152	0.117	0.111
Dummy – prior degree	9.314	8.470	9.354
Std. error	22.431	20.783	21.347
P-value	0.679	0.684	0.662
Dummy – dom/int	10.981	11.125	10.401
Std. error	9.344	8.650	8.898
P-value	0.243	0.198	0.246
Dummy – ESL	9.472	9.441	9.321
Std. error	7.704	7.131	7.331
P-value	0.222	0.186	0.207
Dummy – parents ed	—6.922	—6.830	—7.135
Std. error	4.055	3.754	3.866
P-value	0.092	0.069	0.068
Time constraints			
hours worked	—0.082	—0.085	—0.068
Std. error	0.186	0.173	0.178
P-value	0.663	0.620	0.704
Commute (mins)	—0.131	0.128	0.145
Std. error	0.092	0.085	0.088
P-value	0.158	0.132	0.103
Intercept	81.812	81.513	84.010
test stat (see note)	3.77	54.63	46.07
P-value	0.0001	0.000	0.000
simple R^2	0.3716	0.3707	-
Log likelihood	-	-	-398.617

Note: The variable study load was dropped after initial results showed this variable was not significant and dropping the variable resulted in an improved goodness of fit. While other variables in the current model are not significant (e.g. OP, commute time and subjects studied), however it was found that dropping these variables resulted in a reduced goodness of fit, hence they were kept in the model. X The 2SLS model reported in the third column used the square of lecture capture use as instrument for lecture capture use, with a correlation coefficient of 0.88. The Hausman test rejects the H1 hypothesis for presence of endogeneity. The Tobit limit specifies a lower limit on the dependent variable (grade) of 0 and an upper limit of 100. The test statistic for the OLS is the F test, for the 2SLS it is the Wald chi value, while for the censored Tobit it is the LR Chi squared test statistic. All models perform significantly better than their alternative empty models. All intercepts terms are significant at 1 per cent.

Table 5: Results on contemporaneous versus 'subsequent' use of lecture capture

variable	*A*	*B*	*C*
LA	2.528	2.474	2.528
Std. error	0.991	0.979	0.982
P-value	0.013	0.013	0.012
study	0.526	0.500	0.577
Std. error	0.215	0.213	0.217
P-value	0.017	0.021	0.009
LC_cont	1.381	1.095	1.333
Std. error	0.483	0.659	0.488
P-value	0.005	0.100	0.008
LC_sub	0.341	—0.554	0.435
Std. error	0.536	0.814	0.536
P-value	0.526	0.498	0.419
Selected variables			
Dummy – Gender	—5.389	—9.023	—5.968
Std. error	3.474	4.063	3.483
P-value	0.125	0.029	0.090
Dummy – ESL	9.515	9.578	12.170
Std. error	7.264	7.200	8.435
P-value	0.194	0.187	0.153
hours worked	—0.062	—0.073	—0.063
Std. error	0.177	0.174	0.176
P-value	0.725	0.675	0.720
Commute (mins)	0.152	0.159	0.156
Std. error	0.087	0.086	0.087
P-value	0.085	0.068	0.076
Interaction terms			
LC_cont-G		0.636	
Std. error		0.959	
P-value		0.509	
LC_sub-G		1.517	
Std. error		1.079	
P-value		0.164	
LC_cont-ESL			1.426
Std. error			2.531
P-value			0.575
LC_sub-ESL			—5.147
Std. error			3.867
P-value			0.187
LC_cont-LA			
Std. error			
P-value			
LC_sub-LA			
Std. error			
P-value			
LC_cont-COM			
Std. error			
P-value			
LC_sub-COM			
Std. error			
P-value			
Intercept	84.478	84.300	82.402
LR Chi2	47.90	50.58	49.66
P-value	0.0000	0.000	0.000
Log likelihood	-397.7	-396.4	-396.8

Note: This table reports a selected number of coefficients from the regression (specified in text). Due to space constraints not coefficients could be reported. All intercepts terms are significant at 1 per cent.

Table 6: Results on productivity of study time.

variable	*G*	*H*	*I*	*J*
LA	2. 478	2.489	2.333	2.021
Std. error	0. 992	0.985	0.998	0.960
P-value	0.014	0.013	0.022	0.034
study	0.863	0.845	0.659	
Std. error	0.277	0.266	0.260	
P-value	0.003	0.002	0.013	
LC	3.504			
Std. error	1.279			
P-value	0.008			
LC_cont		5.905	2.116	2.271
Std. error		2.057	0.894	0.841
P-value		0.005	0.020	0.008
LC_sub		0.379	2.152	2.709
Std. error		0.918	2.574	0.889
P-value		0.681	0.406	0.846
Interaction terms				
LC-study	—0.126			
Std. error	0.070			
P-value	0.076			
LC_cont-Study		—0.210		
Std. error		0.106		
P-value		0.051		
LC_sub-Study			—0.089	
Std. error			0.137	
P-value			0.519	
Regular study hours				4.618
Std. error				1.419
P-value				0.002
Subsequent study hours				0.052
Std. error				0.267
P-value				0.846
RC3				
Std. error				
P-value				
Intercept	76.294	76.200	84.662	82.713
LR Chi2	48.54	50.63	47.21	55.02
P-value	0.0000	0.000	0.000	0.000
Log likelihood	-397.3	-396.3	-398.0	-394.1

Note: This table reports a selected number of coefficients from the regression (specified in text). Due to space constraints not coefficients could be reported. All intercepts terms are significant at the alpha = 0.01.

Appendix 1 Correlation matrix.

	mark	attend~s	gender	age	native~r	domint	subjec~d	studyl~d	parents	op	hoursw~d	prior	commute	totalhitsn~s	finalh
mark	1														
attendance~s	0.2735	1													
gender	-0.1719	0.0372	1												
age	-0.2304	-0.0573	0.0067	1											
nativespea~r	0.1461	0.1209	-0.0316	-0.0467	1										
domint	0.0647	0.0308	-0.062	0.006	-0.6166	1									
subjectsst~d	-0.0512	-0.1378	0.0269	0.3857	-0.0337	0.0255	1								
studyload	0.0393	-0.0651	-0.1223	-0.1229	-0.0813	0.0887	-0.1018	1							
parents	-0.1932	0.007	0.1234	-0.0507	-0.216	0.1636	0.0767	-0.016	1						
op	0.1142	-0.0102	0.194	0.1216	0.1134	-0.0835	-0.1028	-0.1153	-0.1569	1					
hoursworked	-0.1081	-0.1643	-0.0712	0.2439	-0.1524	0.1389	0.1596	-0.1447	-0.0157	0.0798	1				
prior	0.0479	0.1655	0.093	0.1869	-0.0346	0.0262	0.5343	-0.0083	0.1602	-0.099	-0.147	1			
commute	0.0625	0.0187	-0.1109	0.0774	-0.2245	0.117	0.0094	-0.088	-0.0585	-0.0819	0.0237	-0.0085	1		
totalhitsn~s	0.1808	-0.1348	-0.0051	0.0938	-0.0073	0.0825	0.0809	0.0422	0.0748	-0.0492	0.038	-0.0634	-0.0822	1	
finalh	0.3228	0.1613	-0.1171	0.1675	0.0975	0.0693	0.2733	-0.1369	-0.0647	0.1103	0.1021	0.257	-0.1112	0.166	1