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Abstract

The recent introduction of online lecture recordings have endowed students with greater flexibility about *when* they can access learning material and *what type* of tasks they can undertake during private study. Consistent with behavioral models of intertemporal choice, we find evidence that this new technology alters study behavior in two respects. First, it enables students to substitute to relatively low cost study tasks, such as viewing online lecture recordings, from relatively high cost study tasks, such as completing homework exercises. This substitution reduces the effectiveness of private study time in contributing towards academic achievement. Second, online lecture recordings facilitate procrastination by enabling students to 'binge study' by delaying more of their study until immediately prior to exams. However, binge study is not associated with lower academic achievement. Implications for undergraduate curriculum design are discussed.

Key words: Procrastination, binge study, online lecture recordings

JEL Codes: A22, D91, I20

PsycINFO Classification code: 3550; 3530; 2340

1. Introduction

While most people procrastinate, college students are notorious procrastinators. Estimates indicate that 80 to 95 per cent of college students engage in procrastination (Ellis and Knaus, 1977; Steel, 2007). The practice of staying up all night to study immediately before an exam has become a commonly accepted and time-honoured tradition of college life (Zarick and Stonebraker, 2009). Such ‘binge study’ is typically viewed with concern among educators who emphasize the importance of regular study in facilitating a deeper, more cognitively-engaged mode of learning that embeds knowledge in a way that is not quickly forgotten after the exam (Marton and Saljo, 1976; Biggs, 1993; Aharony, 2006). Even among those who engage in procrastination, this behavior is perceived as being harmful and 95 per cent of procrastinators report a desire to reduce this type of behavior (Steel, 2007).

We investigate how the recent emergence of online lecture recordings can foster procrastination behavior by endowing students with greater flexibility in timing their study. A number of empirical studies have focused on how online lecture recordings have affected lecture attendance and academic achievement (Larkin, 2010; von Konsky et al., 2009). However, its effects on the type of study tasks that students undertake and the timing of study have not received much attention. By observing student’s temporal use of online lecture recording, how their study hours are distributed across the semester, and their academic achievement, we are able to shed greater light on these issues.

Based on the behavioral economics of intertemporal choice (Frederick et al., 2002; Akin, 2012) we posit that there are two ways in which online lecture recordings affect the temporal allocation of study. First, such technology may affect the *type* of study students undertake during their private study. It offers a new type of study activity involving using (or re-viewing) lectures online, which requires relatively less effort than alternative study activities, such as problem-solving tasks. Because of asymmetries in the evaluation of future gains and losses (Loewenstein and Thaler 1989), we argue that students will tend to discount the long term benefits of study tasks and focus more on the short term costs associated with study tasks. Since viewing online recordings is a study task that has a relatively low, albeit positive, contribution to the student’s academic achievement, an outcome of this substitution process is that the overall effect of private study on academic achievement (the ‘productivity’ of study hours) will diminish the more students are prone to using this technology. We test this hypothesis by examining the relationship between private study hours and academic achievement, and how it is mediated by the use of online web recordings. Our results show that, although the use of online lecture recordings is positively correlated with academic performance, there is indeed a negative and significant correlation between using lecture capture and the productivity of private study hours.

Second, we argue that online lecture recording fosters the tendency for students to change *when* they study during a learning cycle, defined as the period between assessment tasks, so that a higher proportion of study takes place immediately prior to the exam – that is, binge study. We empirically investigate this by examining how study patterns change across two learning cycles, which allows us to observe how students change their study patterns in the second learning cycle in light of feedback on their academic performance in the first cycle. Such feedback may foster greater self-control in future learning periods and enables students to develop schemes to overcome procrastination (O'Donoghue and Rabin 1999b, p. 807). This updating process is particularly important in our data as the students we observe are first-year undergraduate students who are adapting to new study environments at university and may be uncertain about the difficulty of the assessment items.

We find evidence that the more students tend to use online lecture recordings, the more likely they are to shift their study to the period just prior to the final exam. This result supports our hypothesis that the availability of online lecture recordings fosters binge study among students. At the same time, we find evidence that online lecture recordings are only positively correlated with academic achievement if used during the non-binge study period. As such, this technology represents a double-edged sword for students: while it encourages students to delay binge study, using this technology for binge study does not appear to deliver better academic results. We also find evidence that procrastination, to some extent, can have positive payoffs: the more students binge study, the higher is their academic achievement. This suggests that such behavior is not necessarily irrational and may in part reflect the presence of assessment items that suit binge study patterns and foster surface learning approaches rather than to deep learning approaches.

The paper is structured as follows. Section 2 surveys previous studies of online lecture recording and the effects on lecture attendance and academic achievement. Section 3 employs intertemporal choice theory to derive hypotheses about how online lecture recordings affect the type of study tasks students engage in, as well as the timing of study. Section 4 discusses data and the empirical strategy to studying the effect of online lecture recordings on procrastination behavior. Section 5 presents the results, while Section 6 discusses implications for undergraduate curriculum design.

2. Background

In the past few decades, the newspaper and music industries are just two of the sectors that have undergone important structural changes in the wake of the internet revolution (Litan and Rivlin, 2001). It is perhaps not surprising that web-related technologies are reshaping the delivery of tertiary education (Larsen and Vincent-Lancrin, 2005). A prime example of this process is the emergence of online lecture recordings, which involves recording lectures and posting them online for viewing by students on or off campus. How has this new technology affected the timing and quality of study patterns? In one sense, the ability to access information available in the lecture at some later date is not new at all. Students have traditionally done so by taking notes during the lecture or even recording the lecture on portable tape recorders. At the same time, most of these alternatives were relatively imperfect as students still had to be present at the lecture in the first place to record notes and tapes. In the case of online lecture recordings, students are not required to be present at the lecture in order to have online access to recordings. In addition, anecdotal evidence suggests that this technology enables students to fit study time into their relatively busy lifestyles. Online lecture recordings allow students to download recordings onto their portable mp3 players, which they can review whilst engaged in other activities, such as commuting (von Konsky et al., 2009). Thus, online lecture recordings represent an important change in the learning environment that, on the one hand, reduces the incentives students have to attend lectures and, on the other hand, allow students more flexibility in their time allocation.

In the existing literature studying the impact of online lecture recordings, scholars have been primarily concerned with how it affects lecture attendance. Many point out that 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 for those students who have more work commitments and/or a further distance to travel to university.[1] In a larger survey of 815 students across various universities, Gosper (2008) found that over 56 per cent of students reported that they attend lectures less frequently due to online lecture recordings. von Kronsky et al. (2009) examined actual attendance records and found evidence that a small percentage of students watched lectures exclusively online rather than attending the class, while others used online lecture recordings to 'catch-up' on the occasional missed lectures.

At the same time, empirical studies have yielded quite mixed results about the effect of this technology on academic achievement (von Konsky et al., 2009). In a study of an undergraduate engineering class, McCredden and Baldock (2009) found that students who used online lecture recordings tended to perform worse than other students. Interviews revealed this was due to technical issues related to the recordings - students reported problems with the lecture in terms of seeing the blackboard, understanding the lecturer and the difficulty of the material. Figilio et al (2010) report on the effects of 'live' versus 'online' lectures on academic achievement in a large first-year economics course in the US. Their results show that the overall effect of live instruction relative to online instruction on academic achievement 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

[1] It is worth noting the long term downward trend in student attendance that pre-dates the introductions of online lecture recordings (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.

academic achievement (measured via high school performance and university GPA) tended to perform significantly worse in their assessment when they watched lectures ‘online’ rather than ‘live’. A similar negative effect was found amongst male students. In addition students from certain ethnic groups 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.

To properly understand how online web recordings affect academic achievement, it is worth briefly reflecting on how such a technology interacts with the underlying cognitive approach students take to learning. A prominent distinction is made in the literature between ‘deep’ and ‘surface’ approaches to learning (Marton and Saljo, 1976; Biggs, 1993; Aharony, 2006). In brief, the former refers to an approach to learning that is more intrinsically motivated, driven by curiosity and a search for meaning. In contrast, ‘surface’ learning is more extrinsically motivated by a desire for academic achievement and focuses on assessment requirements. ‘Surface’ learning tends to involve rote learning and memorizing of content for assessment, which is likely to be forgotten quickly after exams (Chin and Brown, 2000).

Different study tasks and temporal patterns of study can either foster or inhibit these distinctive approaches to learning. By designing the course curriculum with these factors in mind, educators can encourage students to adopt a particular approach. For example, providing an overwhelming volume of teaching material or emphasizing tasks that require relatively low cognitive effort, such as passively listening to the lecture or reading a textbook, encourages surface learning and the tendency for memorization of content (Biggs and Tang, 2011). In terms of assessment, multiple choice questions and short answer exam questions often tend to promote surface learning as they often rely on recall and recognition skills (Scouller, 1997; Biggs and Tang, 2011). On the other hand, deep learning involves moving beyond the passive absorption of information toward reflection on the teaching material and using it to analyse and discuss problems and experiences encountered in their daily lives (Aharony, 2006). Study activities associated with deep learning typically feature problem-based learning (at least in the context of economics), in which students seek to understand and reflect on teaching material before applying it to solve a set problem.

Concerning the temporal distribution of study, educators can encourage students to adopt deep approaches to learning by encouraging regular study. This is because deep learning requires consolidation and reinforcement of understanding which in turn requires practice. To understand the big ideas, or threshold concepts, in a discipline like economics, students need to spend time repeatedly revisiting the concept in different contexts (Meyer, 2006). Binge study is therefore not likely to be an effective way of acquiring threshold concepts. To learn effectively, students must not only spend enough time learning but the learning time must occur regularly throughout the semester (Kember et al., 1995). Research on students who concentrate their study close to the examination period reveals that they tend to have little confidence in their capability to study, which likely reflects a surface approach to studying (Howell et al., 2006; Klassen et al., 2009).

Therefore, it may be that online lecture recordings are useful to both surface and deep learners, but at different points of the learning cycle. This would help explain the mixed results about the effect of online lecture recordings on students' academic achievement. For deep learners who tend to engage in study regularly throughout the semester, such technology may represent a useful supplement to lectures as it helps them review the material and reduces the need to write notes in lectures, enabling them to potentially focus on deeper engagement with the material. On the other hand, for surface learners who tend to focus their study immediately prior to the exam, the availability of online lecture recordings at the end of the semester may help them memorize key parts of the learning material more efficiently and reduce the need to use other learning material such as textbooks and tutorial exercises.

3. Theory and Hypotheses

We draw on the behavioral economics literature on time discounting and time preferences to consider how the emergence of online lecture recordings has affected the timing of study and the type of tasks students undertake during study. Procrastination is the act of delaying a task (O'Donoghue and Rabin, 2001). Most models of procrastination assume that a potential procrastinator has only one task under consideration, and hence the only concern is when the person completes the task. Formalized by Laibson (1997) and O'Donoghue and Rabin (1999a, 1999b) and based on earlier work by Strotz (1956), Phelps and Pollak (1968) and Akerlof (1991), these models analyse how agents choose in which time period (*t*) to carry out a particular action using an inter-temporal utility function that is a weighted sum of utility from each period (x_T):

$$U^T(x_1, x_2 \ldots, x_T) = x_1 + \beta \sum_{t=2}^{T} \delta^{t-1} x_t$$

where T is the planning horizon, δ is the discount factor ($0 < \delta < 1$), and β is a coefficient for present bias ($0 < \beta < 1$) that represents a time-inconsistent preference for immediate gratification. If $\beta < 1$, then more weight is given to utility received today than to that received in the future. If $\beta < \delta$ then time inconsistent impatience may emerge in which agents plan to do something in the future but subsequently change their mind and delay undertaking the action. To illustrate time inconsistency, Cartwright (2011, p. 147) discusses the case of Maria who has to decide whether to complete her homework on Friday, Saturday, Sunday or Monday (Table 1):

Table 1: Maria's homework problem

Plan		*Utility on…*			Total
	Friday	Saturday	Sunday	Monday	Utility
Do it Friday	-5	5	10	4	14
Do it Saturday	0	-5	10	10	15
Do it Sunday	0	5	-5	10	10
Do it Monday	0	5	10	-5	10

In the case where there is no present bias ($\beta = 1$) and no discounting of future utility ($\delta = 1$), Maria would gain the most utility be completing the homework on Saturday where the total utility is 15. As shown in the Table 2, if $\delta = \beta = 0.9$ then Maria will plan to do her homework on Saturday (utility = 9.8) and on Saturday she will decide to indeed complete this homework (utility = 10.4). In the case where $\beta = 0.8 < \delta = 0.9$ time inconsistency will emerge in that on Friday Maria will plan to do her homework on Saturday, but on Saturday she delays doing it until Monday where her payoff is relatively higher (9.0). Thus procrastination has taken place since the student has delayed a task.

Table 2: The effects of the discount factor (δ) and the present bias (β)

Plan	$\delta = \beta = 0.9$		$\beta = 0.8 < \delta = 0.9$	
	On Friday	On Saturday	On Friday	On Saturday
Do it Friday	9.0	-	7.4	-
Do it Saturday	9.8	10.4	8.7	8.7
Do it Sunday	7.0	8.2	6.2	7.9
Do it Monday	8.1	9.5	7.2	9.0

A key enabling condition for this dynamic is that agents face no external constraints about delaying an activity and have a tolerance for delaying the task until a future time period. If for some reason agents are not able to delay an activity, procrastination cannot take place. If they do have the ability to delay, the tolerance is greater than zero and $\beta < \delta$, it is possible that this cycle of planning and then delaying an activity may repeat itself indefinitely over time as long as the agent is willing to tolerate some delay in undertaking and does not learn about her tendency to procrastinate from past experiences (O'Donoghue and Rabin, 2001, p. 131).

In this regard, we argue that the availability of online lecture recording enables procrastination by allowing students greater flexibility in choosing when to study. Prior to the introduction of online lecture recordings, a zero tolerance for delay was essentially imposed on the students by the fact that the teaching material was only available at the lecture. In this case, as long as students had some preference for accessing the material, they had no choice about *when* they were able to do so. It is therefore plausible that the introduction of online lecture recordings has allowed those students who are prone to delaying study the opportunity to do so. Students have less incentive to study at regular intervals throughout the learning cycle. This is supported by evidence of a negative correlation between lecture attendance and viewing lecture capture online (see Figure 1). In our data, we are not able to directly observe study patterns in the absence of online web recordings because we do not have a control group.[2] However, we can empirically verify this relationship by examining how the frequency of viewing online lectures is related to the extent to which students concentrate their study time into the final weeks immediately preceding the mid-semester and final exams.[3] If the viewing of online lecture recordings does enable procrastination, then we would expect those who use this service more frequently to exhibit a higher degree of binge study.

> **Hypothesis A:** The more often online lecture recordings are accessed, the more students tend to concentrate their study time in the period immediately before exams.

Beyond affecting the timing of study, a second important consideration is how online lecture recordings affect the choice of study tasks. Online lecture recordings provide a new alternative type of study task that students can complete during their private study time. Previously, these tasks include reviewing lecture notes, answering tutorial questions and reading the textbook. In the particular course to which our data apply, instructors placed much emphasis on completing tutorial exercises as preparation for the mid-semester and final exam.

Since study can be viewed as an investment decision involving risk and featuring agents incurring short term costs (time and cognitive effort) in return for longer run benefits that are uncertain (academic achievement), it is worth considering how this decision would be affected by asymmetries in how agents evaluate future gains and losses. In particular, there is a large body of evidence suggesting that agents discount gains at a higher rate than losses (Loewenstein and Thaler, 1989; Loewenstein and Prelec, 1992, Frederick et al., 2002, p. 362). For example, Thaler (1981) asked subjects to imagine they had received a traffic ticket that could be paid either now or later and to state how much they would be willing to pay if payment could be delayed (by three months, one year, or three years). The discount rates imputed from these answers were much lower than the discount rate imputed from comparable questions about monetary gains. Other studies that have found similar results include Benzion et al. (1989) and Loewenstein (1987).

This gain/loss asymmetry suggests that students will prefer those tasks that require lower immediate costs, even if the long term benefit is lower than for other tasks that require more costs. For the average student choosing a study task to complete, the option of viewing the lecture recording online is a passive study task that requires relatively little cognitive effort in comparison to other active study tasks, such as answering questions and solving problems. At the same time, the future benefits of

[2] A control group was prohibited by academic managers who argued that it was inequitable for the control group not to have access to online recordings.
[3] An OLS model of lecture attendance using several demographic and study variables found that the viewing of online lecture ~~attendance~~ has a negative and significant impact on lecture attendance at the α= 10 per cent level.

viewing lecture recordings online are likely to be less than those derived from working through questions and problems. As a consequence, in terms of academic achievement, if students do consistently substitute away from problem-solving activities in favour of viewing online lecture recordings, there would be lower future benefits in terms of academic achievement. Because of the lower long term benefits of viewing online recordings, private study will become less effective in terms of academic achievement.

> **Hypothesis B:** The more often online lecture recordings are accessed by students, the less effective is their study time in delivering academic achievement.[4]

4. Method and Data sources

Data were collected from four sources: a survey, lecture capture access statistics, a study diary and academic achievement of students participating in the survey. The survey was conducted in the first lecture of the course. The number of students who completed the survey was 229 and the total number of students enrolled in the class was 420. The descriptive statistics are given in Table 3. To assess the representativeness of this sample, we examined how the distribution of final grades received by students in this sample compared with the distribution of final grades in the total population of students. We found the comparison to be close which 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 by recording the presence of students during a sample of 5 out of a total of 11 lectures during the semester (see "Lecture Attendance" in Table 3).

Table 3: Descriptive statistics of variables from student survey and lecture role

Variable	Obs	Mean	Std. Dev.	Min	Max
Grade (Range 0-100)	389	65.6	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	0.5	0	1
Age	193	20.75	6.04	0	53
English as a Second Language (ESL) dummy (1=yes, 0=no)	215	0.18	0.38	0	1
Domestic dummy(1=yes, 0=no)	211	0.83	0.37	0	1
Nr of Previous subject studied	206	3.15	5.28	0	30
Parents completed uni (1=yes, 0=no)	216	0.29	0.45	0	1
High School grades (OP 1 = highest score)	128	10.52	3.5	2	18
Hours worked	198	14.39	11.21	0	50

[4] The same hypothesis can be made from another perspective found in O'Donoghue and Rabin 2001). They show how the introduction of new alternative tasks may induce procrastination behavior in agents. Their results depend on how self-aware agents are about their own tendency to procrastinate (O'Donoghue and Rabin, 2001, p. 141).

Prior degree dummy (1=yes, 0=no)	216	0.04	0.2	0	1
Commute time (reported in minutes)	217	28.38	19.22	1	120

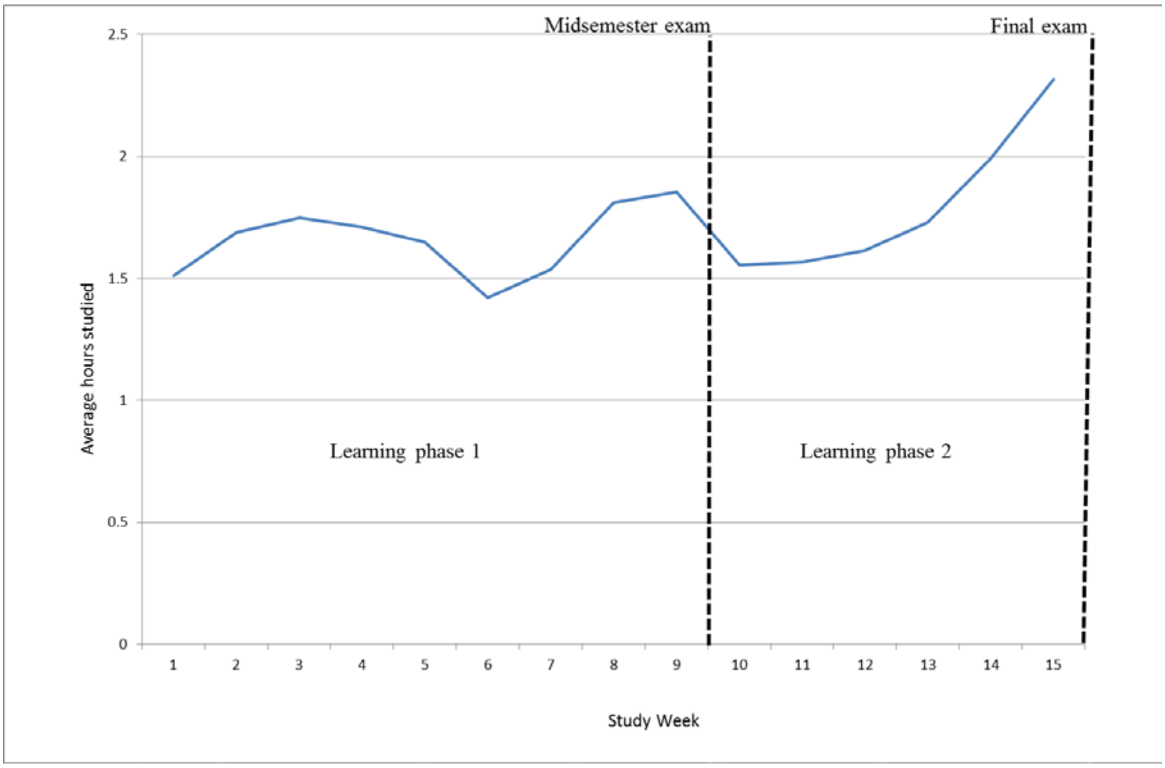
Table 4: Access data for online lecture recordings

Variable	Obs	Mean	Std. Dev.	Min	Max
Total LC views	388	4.86	9.84	0	88
LCC	388	2.45	4.91	0	45
LCS	388	2.4	6	0	62

In addition, usage data from the system hosting the online web recordings provided us with information on the date at which students accessed lecture recordings. This provides us with 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 the student has accessed online web recordings ("LC") in order to study how such usage influences academic achievement. In addition, we examine whether the overall effect of this service on academic achievement is different in terms of the timing of the use of lecture capture. Hence we create two variables (Table 4): i) contemporaneous use (LCC) which is defined as the number of hits on lecture capture files within two weeks of the lecture; ii) subsequent use (LCS) – use of online recordings at a date that is more than two weeks after the lecture (see Table 4).

The final source of data was the weekly online diaries that 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 students dedicated to studying the subject (see Figure 2). The question posed was "Apart from attending lectures and tutorials, how much time did you spend studying 1303AFE at home in the past week?" This question was administered online and appeared when students accessed lecture capture files. Students were given an incentive to complete this weekly diary with the chance to win fifty book vouchers (worth either A$50 or A$100) that could be redeemed at the campus bookstore for textbooks, stationary, sweets and T-shirts. The response rate on this item was relatively high, with over 90 per cent of students completing the weekly diaries at some stage during the semester. At the same time, most diaries contained missing observations for some weeks. A moving average process was used to reduce the number of missing averages. This involved replacing a missing value with the average number of study hours the students undertook in the week immediately prior and after the week in question. In the case where there were multiple missing weeks in sequence, this process could not be applied.

Figure 2: Average weekly hours studied over the semester



4.1 Empirical approach

Concerning **hypothesis B**, we examine how the type of study tasks that students choose to undertake are affected by online lecture viewing by examining how the frequency of online lecture viewing affects the productivity of study hours, defined as the contribution that an additional hour of study has on the student's academic performance. If the use of online recordings during private study does not cause students to delay other study tasks, such as the completion of tutorial questions, then we would expect the frequency of lecture capture use to have no effect on the productivity of study. On the other hand, if indeed online lecture capture recordings causes students to regularly substitute harder study tasks, such as doing questions and problems that are associated with deep learning in favour of easier tasks that have a lower long run benefit, then we can expect there to be a negative effect between the use of online lecture recordings and the productivity of study hours.

To investigate this, we empirically study how academic performance is dependent on the students' use of online web recordings and the number of hours they dedicate to private study, among other variables. The following regression model is estimated:

$$g_i = \beta_0 + \beta_1 LA_i + \beta_2 LC_i + \beta_3 study_i + \beta_4 binge_i + \beta_5 time_i + \beta_6 dem_i + \beta_7 LC_i \times study_i + \epsilon \qquad (1)$$

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 online lecture recordings were accessed, *study* is the number hours spent in private study, *binge* is the ratio of average hours undertaken in the binge periods (the two weeks immediately preceding both the mid-semester and final exam) to average hours studied in the non-binge period. The higher this ratio, the more students tended to concentrate their study into the weeks immediately preceding the exams. The variable *time* is a vector of variables that represent time constraints on study performance, such as weekly hours worked and commuting time to university, and *dem* represents the vector of demographic characteristics, such as age, gender, whether English is a second language, whether the student is a domestic or international student, high school grades (OP), and whether parents also have a university degree. The variable $LC_i \times study_i$ is an interaction term between the use of online lecture recordings and study hours. Its coefficient reflects how the use of online lecture recordings affects the productivity of study hours. If hypothesis B is correct, we expect that β_7 is negative and significant as the use of online lecture recording has changed the type of tasks undertaken during private study and reduced the effectiveness of on campus study in attaining academic achievement to students.

We are mindful of the possibility of endogeneity in this regression, since high achieving students may be more likely to use learning resources more frequently, including the online lecture recordings. Endogeneity would imply that the use of online lecture recordings is co-determined by academic achievement. Following other studies (Barnes and Smith, 2009; Smith et al., 2009), we instrument the use of online lecture recordings with its subgroup average across four equally sized age groups. The rationale for this choice of instrument is that there are age-related factors affecting the use of online lecture recordings that are unrelated to academic achievement. While all students face certain barriers to using online recordings, these barriers may be stronger for students of a certain age. For example, older students may find it harder to use such relatively new technology, which represents a natural experiment through which variation in the use of online recordings is observed that is unrelated to the student's academic achievement. The choice of instruments seems to be appropriate as the Anderson test for under identification shows that the instrumental variable is sufficiently correlated with the endogenous variable, with a Chi-square statistic of 0.0085. The second column of Table 5 reports the results of the two stage least squares (2SLS) model using this instrument. The results are similar to the OLS, which suggests that endogeneity does not appear to be present. A Hausman test for endogeneity which compares coefficients between the OLS (in column 2) with the coefficients estimated via 2SLS (column 3) failed to reject the null hypothesis that endogeneity is not present in the regression.[5]

[5] It does however reveal that the endogenous variable is not significant, which is a typical problem if the endogenous variable is weakly identified. Several other ways to instrument for the endogenous variable were attempted, including combining a number of other variables with the chosen instrument, but these alternatives did not escape the weak identification problem and did not yield better results.

An additional consideration is the fact that the value of the dependent variable has a limited 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 5 below compares the basic OLS model with the 2SLS and the censored Tobit model. Regarding the possibility of multicollinearity, the correlation matrix revealed that none of the independent variables were strongly correlated.

Concerning **Hypothesis A**, we examine how the availability of online lecture capture affects the distribution of study hours across the learning cycle. It is important to note that many of the students are in their first semester of study at university and therefore face uncertainty in terms of knowing how effective their study strategies are in achieving good academic achievement. With little experience with university-level assessment items and little knowledge of how much study they need to do to attain a certain grade, it is relatively difficult for students to work out their most effective study strategies. For this reason, it makes more sense to study how factors *alter* the timing of study in the second learning cycle in light of feedback they received from their academic performance in the first learning cycle. Such experience may foster greater self-control in future learning periods and enables students to develop schemes to overcome procrastination (O'Donoghue and Rabin 1999b, p. 807; Akin 2012).

The course in question is an introductory economics course in which the first learning cycle and the mid-semester exam is dedicated to microeconomics, which covers such topics as opportunity cost, the demand supply model, and modelling firm production decisions in the context of perfect competition and monopoly. The second learning cycle and end of semester exam is dedicated to macroeconomics which covers topics such as unemployment, inflation, modelling business cycles and economic growth. Thus there is relatively little overlap in contents between learning cycle 1 (microeconomics) and learning cycle 2 (macroeconomics). At the same time, it is possible that the mid-semester grade they attained in the first learning cycle may influence the degree to which students binge study in the second learning cycle. Some students may be more motivated not to binge study if they receive poor results in the mid-semester exam. On the other hand, it could also be the case that high academic achievement leads to greater binge study as students who simply want to pass the exam find they need to dedicate less effort to achieve satisfactory results. For these reasons, we include the mid-semester grade as an explanatory variable for change the distribution of study.

For each student we calculate the average hours studied in the two weeks immediately before the exam in the binge period ($b_{c,i}$) and average hours studied in the non-binge period $(n_{c,s})$. Figure 2 shows the average hours studied for the entire class across all periods. As expected, study hours tend to increase at the end of each learning cycle in the two binge periods, which is immediately before the mid-semester and end of semester exams. For each learning cycle (c) and each student (i), we calculate the ratio between the average study hours undertaken during the binge period to those in the non-binge period:

$$r_{c,i} = \frac{b_{c,i}}{n_{c,i}}$$

We then take the difference between the ratio for the first learning cycle ($r_{1,i}$) and the second cycle ($r_{2,i}$):

$$d_i = r_{1,i} - r_{2,i}$$

If d_i is negative, the student has engaged in a greater degree of binge studying in the second cycle than in the first. If d_i is positive, they have engaged in less binge studying in the second cycle than in the first. The determinants of d_i are modelled as follows:

$$d_i = \beta_0 + \beta_1 LA_i + \beta_2 LC_i + \beta_3 study_i + \beta_6 time_i + \beta_5 dem_i + \beta_6 mid_i \epsilon \qquad (2)$$

If Hypothesis ~~B~~ A is correct we expect that β_2 is negative and significant as the use of online lecture recording encourages the procrastination of study, leading to a lower d_i value. β_6 will reflect how feedback on academic achievement on the mid-semester test, which occurs at the end of the first learning cycle, will influence the tendency to procrastinate and binge study.

5. Results

Table 5 reports the results for the analysis of academic performance. The results show that online web recordings (*LC*), lecture attendance (*LA*), and private study time (*study hours*) all have a positive and significant effect on academic achievement. The results also show that binge study appears to be a relatively effective strategy, as the coefficient for binge study (*binge*) is positive and significant. This indicates that the more students tended to concentrate their study into the period immediately prior to the exam, the higher their academic achievement. Possible reasons for this result are discussed in the next section.

Concerning the demographic variables, it is interesting to note that age has a negative and relatively significant impact on academic achievement. 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 coefficient is that students who are taking an introductory economics course 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, for whom the subject under investigation is a core requirement. Variables that were found to have no significant influence on academic achievement at the α=10 per cent level include the number of previous subjects studied, the dummy for non-native English speakers, commuting time to university, the dummy for prior degree and hours worked.

Table 6 reports the impact of online lecture recordings on academic achievement according to the timeframe in which the recordings are accessed. Contemporaneous use of online lecture recordings (*LCC*) refers to the case where students accessed the recordings within 14 days of the lecture date. Subsequent use (*LCS*) refers to the case where students access online lecture recordings more than 14 days after the lecture. As discussed Section 2, contemporaneous use (*LCC*) is more likely to reflect the behavior of deep learners who use online lecture recordings as a supplement to (rather than a substitute for) lecture attendance than is the case for subsequent use (*LCS*). Table 6 shows that only contemporaneous use (*LCC*) has a positive and significant impact on academic achievement, while *LCS* has no significant impact. This suggests that the positive effect of online lecture viewing on academic performance only holds if it is used as part of students' regular study, rather than as a revision tool. Online lecture recordings appear to be an ineffective tool for students who delay their study until the binge period.

Table 7 reports the results related to the productivity of study hours (equation (1)). The productivity of private study time is defined as the marginal contribution of each hour of private study to the student's academic achievement. To test hypothesis B, which suggests that use of lecture recordings diminish the productivity of study time, in regression *A* we test the significance of the coefficient on the interaction term ($LC_i \times study_i$). This coefficient is negative and significant at the α=5 per cent level, which suggests that the use of online web recordings is associated with a negative productivity shock to study time. This may be because students switch from undertaking high-cost tasks featuring problem solving towards undertaking low cost tasks such as viewing online web recordings, as discussed in Section 3.

It would be interesting to know whether the negative productivity shock associated with the viewing of online web recordings applies to contemporaneous or subsequent viewings. In regressions *B* and *C* (Table 7) we introduce new interaction terms: private study hours with contemporaneous use of online lecture recordings ($LCC_i \times study_i$) in regression *B* and subsequent use of lecture capture with private study hours ($LCS_i \times study_i$) in regression *C*. Results show that the coefficient of $LCC_i \times study_i$ is negative and significant at the α=5 per cent level. However, the coefficient on $LCS_i \times study_i$ is smaller and insignificant. This suggests that the negative productivity shock is associated with the contemporaneous use of online lecture recordings, but not subsequent use. The implication is that online lecture recordings tend to reduce the effectiveness of study undertaken during the semester.

Table 8 reports the results for the analysis of binge study (equation (2)). The dependent variable is d_i. If negative, this variable indicates that the students have engaged in a greater degree of binge studying in the second cycle than in the first. If this value is positive, it suggests that they have engaged in less binge studying in the second cycle than in the first. Note that the number observations for this regression fell to 49 (previously 97) as many of the students had missing observations in the binge the study period. This reduced sample size inevitably has some effect on the goodness of fit of the model. The adjusted R^2 for regression *D* is 0.196. Despite many variables being insignificant, most of the coefficients had the expected signs (-/+), which gave us confidence in the results. For example, students who have a higher study load appear to binge study more (*subjects studied*), while those more experience (*prior degree*) binge study less.

In relation to Hypothesis A, the coefficient for online web recordings (*LC*) is significantly negative in model *D* at the α=5 per cent level, which suggests that the more students tended to use this technology, the more they engaged in binge studying in the second cycle relative to the first learning cycle. This confirms hypothesis A that the introduction of online lecture recording encourages students to delay study. When juxtaposed with the results in Table 6, it suggests that there is potential for online lecture recordings to represent a type of 'procrastination trap' for students. The use of online web recordings, on the one hand, encourages students to delay their study but, on the other hand, is not an effective tool for revision (as *LCS* is insignificant in Table 6). The existence of this technology could therefore lure students into delaying study, although it turns out its use is not effective unless used as a supplement to lecture attendance.

It is interesting to note in model *D* (Table 8) that the estimate on the mid-semester grade (*midsem*) is positive and significant at the α=10 per cent level. This suggests that the higher the student's grade the less likely they were to binge study. Those students for whom English is a second language (*ESL*) also tended to reduce the degree of binge study of the two observed learning cycles. One result we did find curious was that students who studied more hours (*study hours*) tended to binge study more in model *D*. It seems more intuitive that students who accumulate study hours during the semester would exhibit a lower tendency to binge study. To check for nonlinear effects, in regression *E* we included the square of study hours (*study hours squared*). This term did indeed turn out to have a positive and significant effect at the α=5 per cent level of significance (Table 8), which suggests that if students have accumulated many study hours, they are less likely to binge study at the end of the semester.

6. Discussion and conclusion

An interesting result is that procrastination appears to be an effective strategy for achieving academic performance (Table 5). This result poses a challenge to the common view that procrastination is a harmful behavior that reduces welfare. In particular, we found that the more students concentrated their study time in the weeks immediately prior to the exam, the higher was their academic performance. This is suggests that, under certain conditions, there are perhaps benefits to delaying study. A number of plausible reasons can be offered for this result. Firstly, many students report that they tend to procrastinate because they study more effectively when under pressure (Hanson 1986, Tice and Baumeister, 1997). Secondly, another explanation could be the costs of recalling information: students may find it relatively easier to recall information learnt in the weeks immediately preceding the exam. Most scholars agree that it typically requires more cognitive effort to remember information knowledge learned in the distant past than in the recent past (e.g. Mullainathan 2002). It is thus plausible that agents reduce recall costs by learning complex abstract information only in the last time period. Thirdly, because students may expect hints about the content of the exam in the weeks immediately preceding the exam, there may be value in waiting before engaging in substantial study for the exam. By waiting students can avoid studying content that is not examinable. Just like firms who may value the option of delaying an investment decision given some likelihood that new information will emerge in the future (Dixit 1994), there may be value in student delaying study until they possess complete information about the nature of the assessment item and its contents. These alternative accounts, should be explored in future studies and suggest that procrastination may be consistent with rational behavior (Fischer 2001).

Secondly, a number of our results suggest that while this technology encourages students to binge study, it is not actually an effective tool for binge study. On the one hand, the more students used online lecture recording, the more likely they are to stop attending lectures and increase the extent to which they engage in binge study in the second learning cycle (see results for *LC* in Table 8). On the other hand, using online lecture recording only has a positive effect on academic performance if it is used as part of students' regular study, rather than as a revision tool (see results for *LCS* in Table 6). Online lecture recordings appear to be an ineffective tool for students who delay their study until the binge period. Indeed, the viewing of online lectures is only positively correlated with academic performance only if it is part of students' regular study (see results for *LCC* in Table 6). Thus educators designing courses that feature online lecture capture need to be aware that this technology represents a double-edged sword for students: while it encourages students to delay their study, the actual use of this technology during binge study does not deliver better academic performance.

Finally, beyond student's welfare, these results have important implication for how educators design the learning environment. For educators interested in promoting a deep approach to learning, our results suggest that this technology reduces the tendency for students to engage in problem-based learning during regular study. In the presence of such technology, additional measures need to be taken to ensure that students engage in problem-solving exercises. In addition, since online web recordings may promote the delay of study, assessment items could be rescheduled in a way that encourages more regular study. For example, rather than having two large exams during the semester, regular and deep learning may be encouraged by holding a series of multiple (say four or six) assessment items. On the other hand, if students do procrastinate in order to work better under pressure, then such regular assessments may also tend to increase the pressure students experience during the semester. Ultimately, the extent to which procrastination should be tolerated depends on the type of teaching material that courses cover, the size of the classes, and the nature of students who attend the course.

Table 5: Determinants of academic performance

variable	OLS	2SLS	Tobit
Attendance	2.222	2.122	2.338
Std. error	1.038	1.086	1.007
P-value	0.035	0.051	0.014
LC	1.356	1.008	1.413
Std. error	0.535	1.847	0.507
P-value	0.013	0.585	0.007
study hours	0.551	0.583	0.574
Std. error	0.245	0.226	0.232
P-value	0.027	0.035	0.016
binge	20.702	20.606	21.307
Std. error	10.306	9.513	9.865
P-value	0.048	0.030	0.034
Demographic variables			
Age	—2.713	—2.663	—2.915
Std. error	0.823	0.800	0.791
P-value	0.001	0.001	0.000
Subject studied	0.186	0.197	0.231
Std. error	0.476	0.442	0.451
P-value	0.696	0.656	0.610
OP	1.011	0.979	1.082
Std. error	0.518	0.505	0.491
P-value	0.054	0.053	0.031
Dummy – Gender	—5.714	—5.615	—6.056
Std. error	3.626	3.381	3.435
P-value	0.119	0.097	0.082
Dummy – prior degree	10.929	8.849	10.952
Std. error	22.207	23.081	21.005
P-value	0.624	0.701	0.603
Dummy – dom/int	11.436	10.974	9.830
Std. error	9.242	8.954	8.748
P-value	0.262	0.220	0.264
Dummy – ESL	8.357	8.625	8.173
Std. error	7.606	7.145	7.195
P-value	0.275	0.227	0.259
Dummy – parents	—8.565	—8.316	—8.831
Std. error	4.067	3.961	3.855
P-value	0.038	0.036	0.025
Time constraints			
hours worked	—0.163	—0.168	—0.150
Std. error	0.187	0.175	0.178
P-value	0.388	0.337	0.403
Commute (mins)	0.148	0.144	0.162
Std. error	0.091	0.087	0.087
P-value	0.108	0.096	0.066
Intercept	73.829	73.217	75.872
test stat (see note)	3.85	3.39	49.90
P-value	0.0001	0.0003	0.0000
simple R^2	0.3966	0.3935	-

Log likelihood	-	-	-396.704

Note: The dependent variable is academic achievement which is the student's final grade for the subject. The sample size was 97 Observations. The adjusted R^2 for the OLS regression was around 0.3. The 2SLS model reported in the third column instrument the use of online lecture recordings with the subgroup average of this variable across 5 age groups. 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 and the 2SLS is the F test, 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 the α= 1 per cent level

Table 6: Results on contemporaneous versus subsequent use of lecture capture

variable	OLS	Tobit
Attendance	2.169	2.285
Std. error	1.040	0.980
P-value	0.040	0.022
LCC	2.030	2.079
Std. error	0.920	0.865
P-value	0.030	0.019
LCS	0.709	0.780
Std. error	0.970	0.913
P-value	0.467	0.396
study hours	0.545	0.567
Std. error	0.245	0.231
P-value	0.029	0.016
binge	19.777	20.374
Std. error	10.368	9.864
P-value	0.060	0.042
Demographic variables		
Age	—2.755	—2.956
Std. error	0.824	0.788
P-value	0.001	0.000
Subject studied	0.113	0.158
Std. error	0.482	0.455
P-value	0.815	0.730
OP	0.989	1.061
Std. error	0.521	0.491
P-value	0.061	0.034
Dummy – Gender	—5.976	—6.314
Std. error	3.636	3.424
P-value	0.104	0.069
Dummy – prior degree	13.588	13.590
Std. error	22.395	21.055
P-value	0.546	0.520
Dummy – dom/int	10.255	9.663
Std. error	9.246	8.699
P-value	0.271	0.270
Dummy – ESL	8.161	7.987
Std. error	7.614	7.158
P-value	0.287	0.268
Dummy – parents	—8.365	—8.607
Std. error	4.082	3.845
P-value	0.044	0.028
Time constraints		
hours worked	—0.145	—0.132
Std. error	0.189	0.178
P-value	0.445	0.459
Commute (mins)	0.145	0.157
Std. error	0.091	0.086
P-value	0.119	0.072
Intercept	75.557	77.570
test stat (see note)	3.65	50.97
P-value	0.0001	0.000
simple R^2	0.4036	-

Log likelihood	-	-396.170

Note: The dependent variable is academic achievement which is the student's final grade for the subject. The sample size is 97 Observations. The adjusted R^2 for the OLS was around 0.3. 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 intercepts terms are significant at α=1 per cent level.

Table 7: Factors affecting the productivity of private study time

variable	*A*	*B*	*C*
LA	2.386	2.416	2.244
Std. error	0.966	0.964	0.977
P-value	0.016	0.014	0.024
study	0.860	0.820	0.675
Std. error	0.269	0.260	0.254
P-value	0.002	0.002	0.009
binge	22.746	20.122	22.014
Std. error	9.717	9.689	9.957
P-value	0.022	0.041	0.030
LC	3.706		
Std. error	1.246		
P-value	0.004		
LCC		5.705	1.912
Std. error		2.012	0.877
P-value		0.006	0.032
LCS		0.562	3.193
Std. error		0.902	0.256
P-value		0.535	0.215
Interaction terms			
LC x study	—0.137		
Std. error	0.068		
P-value	0.048		
LCC x study		—0.206	
Std. error		0.104	
P-value		0.050	
LCS x study			—0.137
Std. error			0.135
P-value			0.316
Intercept	66.73	68.182	75.090
LR Chi2	53.87	54.85	51.98
P-value	0.0000	0.000	0.000
Log likelihood	-394.7	-394.2	-395.7

Note: The dependent variable is academic achievement which is the student's final grade for the subject. This table reports a selected number of coefficients from the Tobit regression. Results for demographic were omitted due to space constraints, coefficients are consistent with those reported in Tables 5 and 6. All intercepts terms are significant at the α = 1 per cent level.

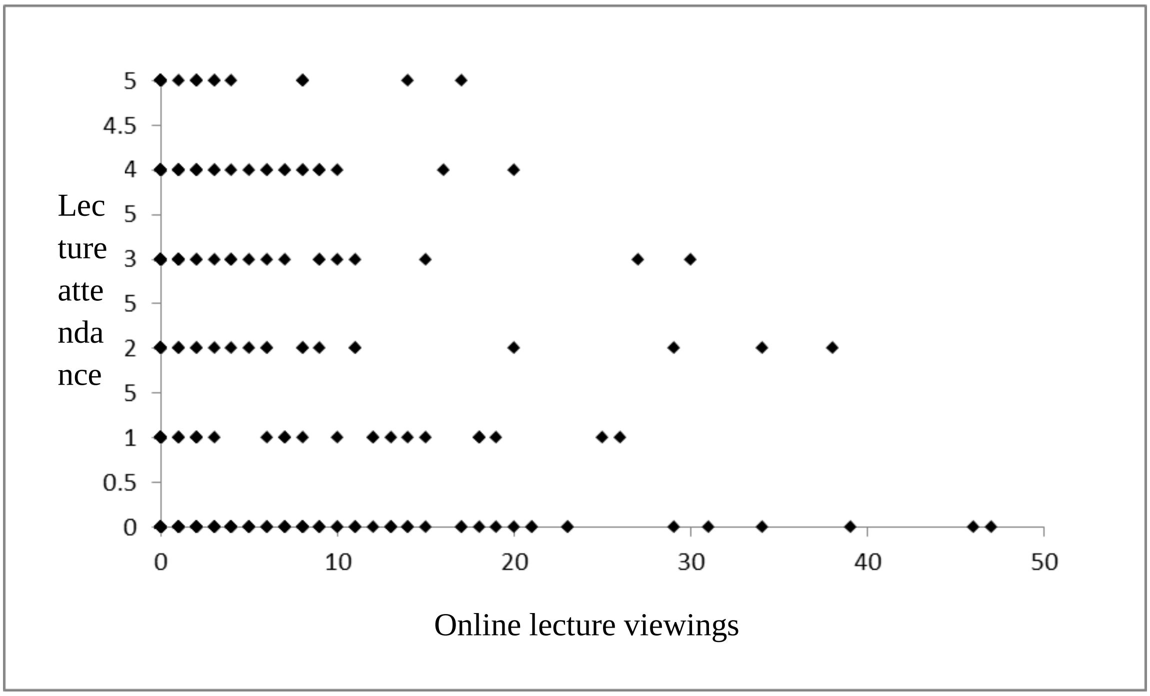
Table 8: Results on binge study

variable	*D*	*E*
Attendance	0.006	0.035
Std. error	0.055	0.053
P-value	0.910	0.522
LC	—0.053	—0.039
Std. error	0.021	0.020
P-value	0.014	0.064
study hours	—0.016	—0.013
Std. error	0.011	0.050
P-value	0.148	0.014
midsem	0.024	0.023
Std. error	0.013	0.013
P-value	0.085	0.080
Demographic variables		
Age	—0.002	—0.016
Std. error	0.023	0.023
P-value	0.919	0.485
Subject studied	—0.011	—0.036
Std. error	0.034	0.034
P-value	0.736	0.295
Dummy – Gender	0.080	0.050
Std. error	0.155	0.147
P-value	0.610	0.735
Dummy – prior degree	0.260	0.422
Std. error	0.590	0.561
P-value	0.662	0.456
Dummy – dom/int	0.666	0.858
Std. error	0.359	0.349
P-value	0.072	0.006
Dummy – ESL	0.737	0.968
Std. error	0.337	0.333
P-value	0.035	0.006
Dummy – parents	—0.326	—0.413
Std. error	0.178	0.172
P-value	0.074	0.002

Time constraints		
hours worked	0.006	0.014
Std. error	0.007	0.007
P-value	0.427	0.072
Commute (mins)	—0.007	—0.009
Std. error	0.004	0.004
P-value	0.103	0.034
Nonlinear terms		
study hours squared		0.002
Std. error		0.001
P-value		0.027
Intercept	-0.698	0.280
test stat (see note)	1.90	2.36
P-value	0.0653	0.0204
simple R^2	0.4137	0.4930

Note: The dependent variable is the change in the extent to which students concentrated their study hours in the binge study period across the first and second learning cycle (d_i). If d_i is positive, they have engaged in less binge studying in the second cycle than in the first. The sample size is 49 Observations. The adjusted R^2 for the OLS was around 0.196 in for regression *K* and 0.284 for regression *L* . The test statistic for the OLS is the F test.

Figure 1: scatterplot of attendance versus lecture capture use.



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