

Generalising the impact of lecture capture availability on student achievement: A method and its application

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Whether the use of lecture capture technology helps improve student performance is a contested area of research. In most cases, the answer relies on the degree to which online recordings supplement or substitute for live or live-streamed lecture delivery. We present a parameter, the technical rate of substitution, which captures this information holding student performance constant. We introduce a method to estimate this measure, which we applied to a pilot sample of students in a first-year quantitative methods class. We find imperfect substitutability: live lectures are, in the context of our sample, a less resource-intensive technology than the corresponding online recording to produce a set exam score. Our main contribution is the proposed parameter and the method to derive it. Its calculation significantly facilitates comparison and consolidation of previous research and provides valuable insights on the relative effectiveness of different learning platforms to inform instructor best practice and higher education policy.

Implications for practice or policy:

- Instructors can use our measure to evaluate their students' effective use of online learning technologies.
- Course designers can use the measure to select the right mix of online and offline delivery methods.
- Educators can use the measure to determine the most effective platform for delivering introductory, substantive or review material.
- Our method helps researchers compare and generalise results from existing studies of the relative performance of online and offline educational technologies.

Keywords: online education technologies, learning platforms, lecture capture, student performance, higher education

Introduction

Lecture capture technology (LCT) is widely used, at times mandated in higher education institutions, especially in the United States of America, the United Kingdom and Australia where most of the research on its impacts has been conducted (Banerjee, 2021). The technology, which records an audio-visual version of a class for student viewing in a learning management system (LMS), is a response to students' demand for a more flexible learning experience (Dobinson & Bogachenko, 2018; Dommert et al., 2020). Beyond students' preferences, the growing deployment of LCT services also responds to a broader process of marketisation of the higher education sector in which digitisation and technology-enhanced learning (TEL) are adopted to stay competitive (Ibrahim et al., 2021).

From its inception, the use of LCT produced contrasted reactions amongst faculty. That students highly value LCT resources is not disputed (Elliott & Neal, 2016; Marchand et al., 2014; Nkomo et al., 2020; Saunders & Hutt, 2015). However, instructors worry about impacts on lecture attendance, student engagement, learning outcomes and how the technology challenges their own teaching approaches (Bond & Grussendorf, 2013; Dommert et al., 2020; Englund et al., 2017; Evergeti & Garside, 2020; Joseph-Richard et al., 2018; Morris et al., 2019; Taplin et al., 2011). These questions have been the subject of a voluminous body of research conducted in all major academic disciplines.

Recent reviews of this literature have found little consensus or even convergence on its findings (Banerjee, 2021; Nordmann et al., 2020; O'Callaghan et al., 2017). To a large degree the absence of concurrence is rooted in the studies' different HEI, LMS and TEL contexts, teaching contents, research methods or cohorts-specific characteristics of these studies (Caglayan & Ustunluoglu, 2020; Nordmann et al., 2020). Learning is also a complex process from which it is difficult to disentangle the contributing role of a specific teaching platform.

One focal point of the debate is whether students use lecture recordings to supplement lecture attendance or to substitute it. There is substantial evidence that students who attend lectures regularly use recordings sparingly and as a supplement, whereas those who attend less regularly (or skip class) use recordings intensively, as a substitute and mostly to revise before exams (Bos et al., 2016; Chester et al., 2011; Gorissen et al., 2012; Saunders & Hutt, 2015; Traphagan et al., 2010; Von Kinsky et al., 2009).

Lecture capture helps both supplementing and substituting students raise their exam score, but for the latter group, which relies more on surface learning (Trenholm et al., 2019; Vajoczki et al., 2011) it is often insufficient to compensate for their lack of attendance (Chen & Lin, 2012; Edwards & Clinton, 2019; Jones & Olczak, 2016; Williams et al., 2012).

The degree to which students substitute lecture attendance with LCT-assisted recordings is undoubtedly an important driver of the performance impacts of LCT. In this paper, we propose a method to isolate a synthetic indicator of platform substitutability. Our proposed parameter, the technical rate of platform substitution (TRS) between the live lecture and the lecture recording, is defined as the number of minutes of watched lecture recording required to achieve the same result as attending the 93-minute live lecture. It captures how input-intensive a recording is relative to lecture attendance in order to produce exam scores. In other words, the TRS captures the time and cognition needed using one lecture delivery platform to achieve the same scores as another platform. Since attending live lectures and viewing recordings are costly activities to students (in terms of time spent and cognitive effort exerted), estimates of this parameter provide the relative implicit cost of using a given learning platform.

We could find no evidence of such estimates in the relevant literature on the effects of LCT on student performance. Yet, in applied research that relies on score functions, for example, Chen and Lin (2012), Jones and Olczak (2016), Kaufmann and Vallade (2020) or Bergeler and Read (2021), we could infer that this parameter could be calculated as the coefficient of live lecture attendance divided by the coefficient of time spent using recordings.

We applied our method to estimate the TRS in the context of a first-year, mandatory Quantitative Methods in Commerce (QMC) course. We stress at the onset that our purpose in estimating this parameter is to illustrate our method and discuss its usefulness for standardising results and improving the comparability of findings in this field of study. Our study does not aim at making any generalisable conclusions from our single reading of this parameter.

The paper is structured as follows: a literature review briefly reviews recent research advances on the experience, attendance and performance impacts of LCT. The next section discusses the research context and presents our data sample. This is followed by a methodology section, which presents our research model and procedure, inclusive of our empirical approach where we discuss the specifications and instruments used. The next two sections report the results of our data analysis together with synthetic responses to a student survey of LCT experience, interpret the results and discuss limitations. A brief, final section concludes our study and scopes out avenues for further work.

Related literature

LCT impacts on student experience

The literature shows that regardless of their scholastic ability students are highly satisfied with the use of LCT in teaching and learning (Davies et al., 2016; Taplin et al., 2011; Toppin, 2011). Flexibility is one of the most attractive features of LCT-assisted resources: lecture recordings allow students to view lectures repeatedly and from various locations (Edwards & Clinton, 2019). Students also value the possibility of learning at their own pace and being able to pause the recordings when their attention span wanes (Dona et al., 2017).

Lecture recordings also have the potential to assist students of different socio-economic and cultural backgrounds or with specific work or health needs (Nightingale et al., 2019). For instance, students who are working (part-time or full-time) and as a result are not able to physically attend lectures can remain part of the student community by accessing recorded lectures. Lecture recordings can also confer similar

benefits to students with disabilities, who have English as a second language, or with specific learning difficulties such as dyslexia.

LCT impacts on attendance

Notwithstanding positive student experience, evidence of impact on student outcomes is mixed, particularly with respect to student attendance and academic performance (O'Callaghan et al., 2017). In many organisations, instructors are concerned that the availability of recordings may discourage students from attending live lectures (Scutter et al., 2010). For example, students may think that live lectures and lecture recordings are equivalent learning resources, but using recordings is more time-efficient or just more convenient in terms of time and place or for juggling other social and professional activities that overlap with live lectures (Edwards & Clinton, 2019).

The literature tends to support these conjectures. In Australia, for example, some researchers have identified the availability of LCT platforms as a reason for increasing absenteeism at lectures and tutorials (Gosper et al., 2010; Taplin et al., 2014). Research in Canada suggests students are more likely to miss live lectures as a result of podcast availability (Holbrook & Dupont, 2009) or if they had access to webcasting technology (Traphagan et al., 2010). In the United Kingdom, second-year students dropped their attendance after the introduction of LCT-assisted resources (Edwards & Clinton, 2019).

However, other studies have found no such effect on lecture attendance (Topale, 2016; Walls et al., 2010; B. T. White, 2009). Vajoczki et al. (2011) also observe that deep learners make a complementary use of LCT (often for review and for preparing examinations), whereas surface learners use LCT as a substitute for live lectures. Hence, it may not be so much the platform as the learning approach that drives impacts on attendance, a conjecture also supported in Williams et al. (2012), Birch and Williams (2015) and Bos et al. (2016).

LCT impacts on performance

Substantiation of any negative impacts of LCT on students' performance is far from established either. A significant research strand, the no significant difference hypothesis, starting with Russell (1999), has found no relationship between use of LCT resources and student performance (Bergeler & Read, 2021; Brackenbury, 2019; Brotherton & Abowd, 2004; Owston et al., 2011; Von Kinsky et al., 2009; L. J. White et al., 2019). Bos et al. (2016) found a low predictive value of either form of lecture delivery on exam performance.

Another substantial research cluster has found negative effects of LCT on student performance, often mediated by negative impacts on class attendance or student engagement (Bosshardt & Chiang, 2018; Edwards & Clinton, 2019; Ferguson & Tryjankowski, 2009; Williams et al., 2012). A third set of results suggests, on the contrary, that LCT usage improves student performance regardless of any effect on attendance (Chen & Lin, 2012; Harjoto, 2017; Jones & Olczak, 2016; Traphagan et al., 2010; Vajoczki et al., 2011).

Often, these studies produce general conclusions but with caveats for specific groups or contexts. Dommeyer (2017) reviews the results of 17 recent studies in a wide range of faculties (predominantly psychology and science disciplines): 8 studies found no effect of LCT on student grades, 4 studies found a positive effect, 4 studies found a negative effect and one found no effects or negative effects (for different classes).

Randomised controlled experiments, for example, Figlio et al. (2013) and Cacault et al. (2021), tend to support the view that taking a course online or reducing traditional class time for more online time has an adverse effect on scores. This is especially the case for complex material and for low-ability students. However, these studies often do not consider the supplemental role of LCT. A recent review of the performance effects of LCT concluded that impacts are complex and related to a range of individual student characteristics such as level of study, ability and approaches to learning (Nordmann & McGeorge, 2018).

Sample information

Course information

The project first underwent a two-stage ethics approval process at the University of Canberra, with approval granted in late 2018). Our pilot sample consists of 129 students who attended a QMC course in the first semester of 2019 in an Australian university. The course is taught to an undergraduate (UG, $n = 106$) and a graduate (G, $n = 23$) cohort. The UG cohort consists mostly of first-year domestic students, whereas the G cohort consists mostly of international students.

QMC teaches basic quantitative methods used in commerce studies including business statistics and linear programming. No prerequisite course or training is required. QMC students are for the most enrolled in business degrees such as accounting, finance, commerce and business. Female students constitute a minority in each cohort (32% among UG students, 26% among G students). Four tutors ran QMC tutorials, with one tutor, Tutor 2, teaching two classes – one for the G cohort (all other classes are UG tutorials).

This course is taught at the most elementary level. At the beginning of the course, a review of basic – high school level – mathematics skills is performed. The course is delivered weekly via a 2-hour lecture and 2-hour tutorial for 13 weeks. All lectures are recorded and are available to students immediately on Canvas, a web-based LMS. The total length of a recorded lecture is 114 minutes. The 13th lecture is a 1½ hour review of material closely related to the final exam. Attendance at lectures or tutorials is monitored but not compulsory.

Course assessment

The assessment consists of four items: two online quizzes (10% each), a group assignment (30%, marked as a group) and a 2.5-hours monitored lab final exam. The students must participate in the group assignment and the final exam, get an overall mark of 50% and score at least 40% at the final exam to pass the unit. The two online tests are identical for both cohorts, but the assignment and final exam questions are marginally different.

Assessment details are summarised in Table 1. Online test 1 covers the basic mathematics skills that are required for this unit and was conducted at an early stage in the semester. We use this test's score as an indicator of students' ability. By contrast, final exam scores are used to measure students' performance.

Table 1
Assessment items

Assessment item	Description	Contents covered	Due date
Online test 1 (10%)	An un-invigilated online test that includes 10 multiple-choice or fill-in-the-blank questions (12 points). Test duration 2 hours	Weeks 1–3: Basic mathematics, compound interest rates, value for money questions	Week 4
Group assignment (30%)	Group assignment for 2–4 students	Weeks 2–5: Visual and numerical summary data methods	Week 8
Online test 2 (10%)	Similar to Online test 1	Weeks 4–7: Data description and elementary probability	Week 10
Final exam (50%)	An invigilated lab exam that includes 10 multiple-choice or fill-in-the-blank questions (20 points) and 4 short-answer questions (80 points)	Weeks 9–12: Basic statistical analysis	Exam period after the semester

Students engagement, performance and demographics

In Table 2, we summarise students’ participation in the scheduled activities of the unit, test scores for the first online test and final exam and some demographics variables. We note first that lecture attendance is poor, with G students attending much more frequently than UG students.

We recorded the total number of Canvas page views by each student during the semester (until the day of the final exam) and use it as an indicator of students’ engagement in the unit. As Table 2 shows, an average student viewed 680 pages during the semester, which is equivalent to around 52 pages per week. Again, the G students participated much more (909 pages) than the UG students (630 pages).

Figure 1 presents the two cohorts’ rate of lecture attendance. We can observe that lecture attendance by UG students never exceeded 40%, as opposed to 60% 70% for the graduate cohort. Only 22% and 57% of UG and G students, respectively, attended the last lecture, whereas the corresponding shares who watched its recording were 59% and 30%, respectively. The total length of time students spent viewing the video was also recorded, inclusive of multiple plays. The average total viewing time was about 78 minutes.

Table 2
Sample statistics

Variable	All	UG	G
Took the final exam	0.891	0.868	1.00
Deferred exam		0.066	
Final exam score excluding deferred (/100)	42.198 (21.79)	40.674 (21.55)	48.296 (22.13)
Final exam score including deferred (/100)	40.539 (22.24)	38.737 (21.98)	48.296 (22.13)
Online test 1 score of (/100)	60.659 (23.34)	59.985 (23.61)	63.768 (22.28)
No. of tutorials attended in the first 7 weeks	5.271 (2.37)	5.123 (2.34)	5.957 (2.44)
No. of Canvas page views	680.19(338.35)	630.415 (330.42)	909.609 (279.32)
Attended the last lecture	0.287	0.226	0.565
Viewed the last recorded lecture	0.465	0.594	0.304
Minutes viewing 13th lecture recording	78.100 (81.65)	79.123 (84.33)	70.357 (61.92)
Gender	0.605	0.679	0.261
Tutor1	0.473	0.575	
Tutor2	0.217	0.047	1.000
Tutor3	0.155	0.189	
Tutor4	0.155	0.189	
Observations	129	106	23

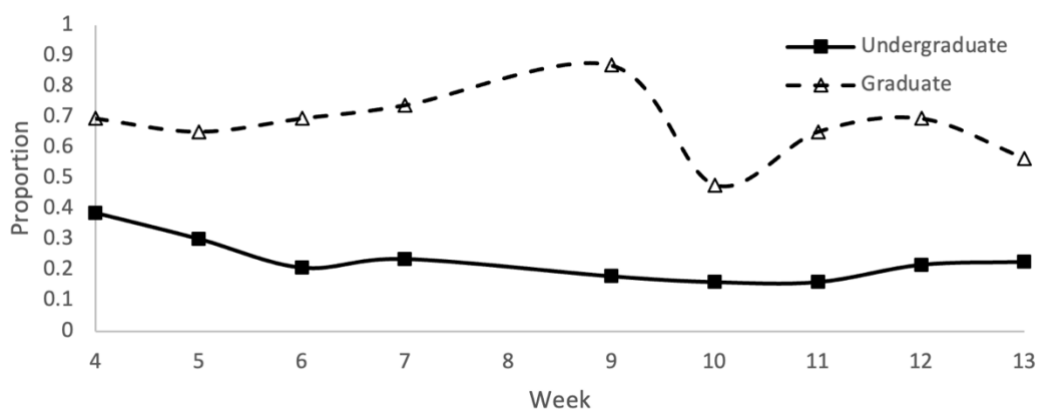


Figure 1. Lecture attendance rate (Week 4 onwards)

Secondly, the G students performed better than the UGs. The mean score achieved at the first online test was about 64 for G students and 60 for UG students. The mean score achieved at the final exam was about 48 for G students and 41 for UG students. About 11% of UG students did not attend the final exam (with about half sitting a deferred exam of difficulty comparable to that of the final exam).

Thirdly, students' final exam scores are positively related to their numerical skills prior to enrolment. Figure 2 displays the smoothed curve of final exam scores against Online test 1 (our measure of course-specific intrinsic ability). There is a strong, positive relationship between exam scores and scores achieved at Online test 1 for all but the lowest ability levels (and strongest for highest ability levels). This relationship is important because it will enable us to build models of student performance whilst controlling for unobserved characteristics (i.e., student ability).

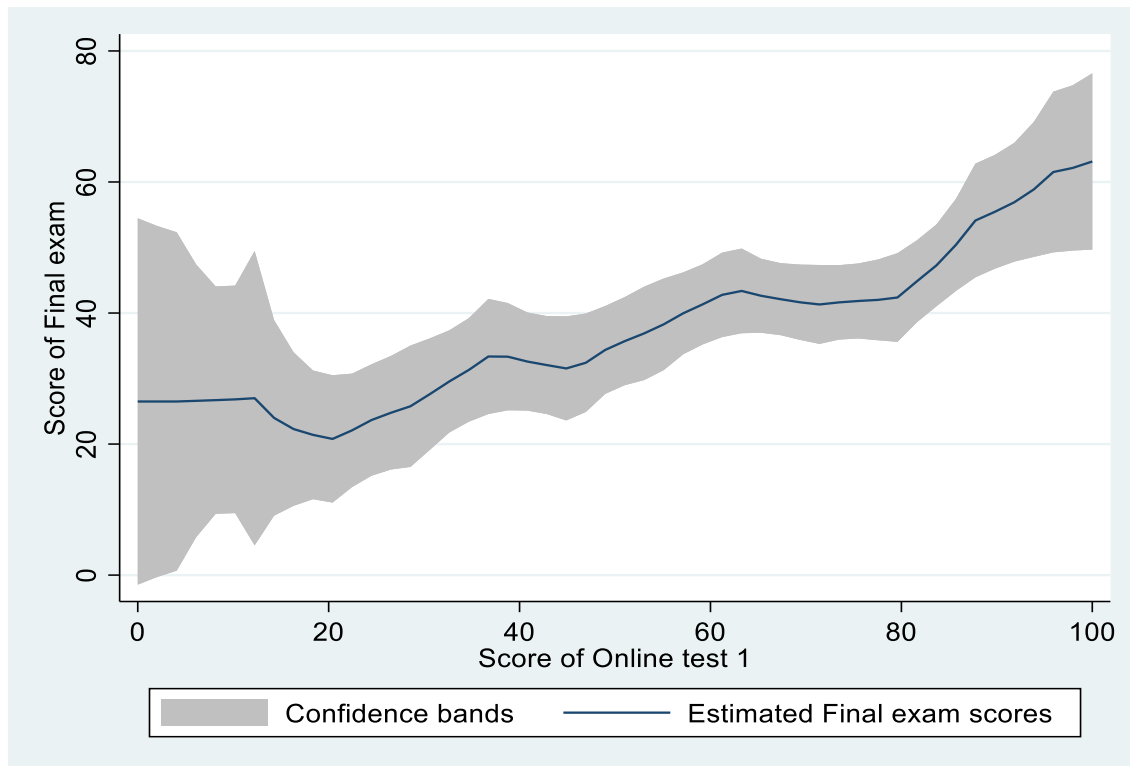


Figure 2. Bivariate relationship between Final exam scores and Online test 1 scores

Relationship between performance and attendance

First, we observe that only a small proportion of students both attended the lectures and watched the LCT-assisted recordings. As Table 3 shows, most (49) of the 60 students who watched the recorded lectures did not attend the live lecture. Conversely, most (26) of the 37 students who attended the live lecture did not use the recording.

Table 3

Engagement with last lecture: live attendance, use of recording, exam scores

	Recorded lecture		Total
	Yes	No.	
Live lecture			
Yes	11 (57.36)	26 (51.49)	37 (53.24)
No	49 (39.97)	43 (29.17)	92 (35.01)
Total	60 (43.32)	69 (38.10)	129

Note. Mean final exam scores are shown in brackets.

Table 3 also reveals a clear relationship between final lecture attendance, use of recorded lectures and students' final exam scores. The average score for students who attended the last lecture was much higher (about 18 points) than for those who did not. The average score of those who watched the lecture was also 5 points higher than otherwise. Unsurprisingly, those who used both delivery platforms scored highest.

Lecture attendance and recording viewing time

In Table 4, we summarise lecture attendance at the last five lectures. For most lectures a substantial proportion of students (roughly one third) did not attend either live or recorded lectures. Those viewing the recorded lectures on average did not watch the whole recording but a portion of it ranging between 55% and 78%.

The time spent watching these portions of whole lectures exceeded the duration of the recorded lecture by a factor of 1.3 to 1.5, which implies that students regularly rewind and replay the same recorded content.

Table 4
Viewing time and proportion of contents viewed

	Attended live lecture	Watched recorded lecture	Attended and/or viewed	% of content watched	Time spent	Time spent (/ % of content)
Week 9	39	38	7	78.000 (35.74)	115.5 (75.09)	1.404 (0.52)
Week 10	28	43	7	69.442 (37.79)	100.512 (80.60)	1.332 (0.59)
Week 11	32	43	7	72.233 (35.64)	119.64 (96.13)	1.521 (0.72)
Week 12	39	38	12	67.894 (41.25)	103.461 (87.95)	1.371 (0.62)
Week 13	37	63	11	55.000 (37.12)	79.071 (82.45)	1.299 (0.57)
No. of students	129	129				

Note. Standard deviations are shown in brackets.

Model and procedure

Empirical specifications

Empirically, if we assume that the outcomes we observe are the result of optimal effort selections (for given student resources, time endowments, cognitive strengths and weaknesses), we can specify the score function of student i as

$$m_i = f(L_i, R_i, X_i) + \varepsilon_i \tag{1}$$

where $m(\cdot)$ is the student’s exam score, L is the level of lecture attendance, R is the time spent watching the recorded lecture, X_i is a vector of observed characteristics (see Table 5) and ε_i is a vector of unobserved student characteristics. Using estimates from the score function (1) we could then calculate the rate TRS_{LR} at which students substitute delivery platform L with delivery platform R for set score targets.

Depending upon the specification of function $f(\cdot)$, we estimate the following five models with increasing flexibility in their functional forms. The simplest specification is the linear model:

$$m_i = \beta_0 + \beta_L L_i + \beta_R R_i + X_i' \gamma_X^l + \varepsilon_i \tag{2}$$

where γ_X^l is a vector of parameters of X_i . The parameter β_L is the effect of live lecture attendance on students’ score and β_R is the effect of recorded lecture attendance on their score, holding other factors constant. This is the mostly widely used model in the literature. In this model, both β_L and β_R are constant and their ratio, which captures the rate at which one delivery platform is substituted for the other, is again a constant. The linear specification may be too restrictive though. For example, as Figure 3 showed earlier, the marginal effect on scores of watching a recorded lecture may depend on the length of time allocated to that activity. To overcome this issue, we introduce a quadratic model:

$$m_i = \alpha_0 + \alpha_L L_i + \alpha_R R_i + \alpha_{RSq} R_i^2 + X_i' \gamma_X^q + \mu_i \tag{3}$$

Unlike the linear specification the quadratic model specifies the effect of recorded lecture attendance on students’ score $\alpha_R + 2\alpha_{RSq} R_i$, which is allowed to vary with the time spent watching the recorded lecture. This property is desirable because under this specification the rate at which lecture delivery

platforms substitute for one another, $TRS_{LR}^q(R_i) = \frac{\alpha_L}{\alpha_R + 2\alpha_{RSq}R_i}$, also varies with time spent watching the recorded lectures.

It is possible that the effect on scores of watching a recorded lecture depends on live lecture attendance as well, so an interaction term could be added to specification (2):

$$m_i = \pi_0 + \pi_L L_i + \pi_{LR} L_i R_i + X_i' \gamma_X^{lr} + \omega_i \quad (3')$$

In such a case, the platform substitution rate is $TRS_{LR}^{lr}(L_i, R_i) = \frac{\pi_L + \pi_{LR} R_i}{\pi_R + \pi_{LR} L_i}$, which depends upon both L and R. These parametric specifications may still be restrictive in terms of functional forms. We thus aim to specify the model further with two semiparametric specifications, which do not impose a specific functional form on the key variables. The first is the partially linear model specified by Robinson (1988):

$$m_i = \delta_0 + \delta_L L_i + g(R_i) + X_i' \gamma_X^p + \varphi_i \quad (4)$$

where $g(\cdot)$ is an unknown function to be estimated. In this model, $TRS_{LR}^{pl}(R_i) = \frac{\delta_L}{g'(R_i)}$, where $g'(R_i)$ is the partial derivative of function $g(\cdot)$, which depends upon the value of watching a recorded lecture. In this model the effect of watching a recorded lecture is allowed to be an unknown function but the effect of attending the live lecture is assumed to be constant.

The second semi-parametric specification is the single-index model, proposed by Ichimura (1993):

$$m_i = q(\theta_0 + \theta_L L_i + \theta_R R_i + X_i' \gamma_X^s) + \rho_i \quad (5)$$

In this model, the effect of the variables is allowed to be an unknown function of an index of the variables. Thus, the marginal effect of each variable will be proportional to the parameters in the index, except for $TRS_{LR}^q = \frac{\theta_L}{\theta_R}$, which is a constant. We estimate the parametric models (2), (2') and (3) using ordinary least squares, whereas the semiparametric models are estimated using the procedures proposed by Robinson (1988), Yatchew (1997) and Ichimura (1993), respectively. The scores of the 7 students who missed the final exam and did not take a deferred exam were predicted using regression results for students with scores of 40 or less.

Instruments used

Our key explanatory variables are attendance at the live revision lecture (*l13*) and time spent watching the recording of that lecture (*vtime13*). The interaction of these two variables (*l13*vtime13*) are included in some models (Models 2' and 3) to capture the non-linear relationship. The score of the first online test is included in the models to control for students' prior skills set (Online, a proxy for their ability). Variables such as tutorials attendance in the first 9 weeks and the number of Canvas pages viewed throughout the semester are used to control other aspects of student effort.

We also included students' gender and cohort as regressors. To be specific, these variables include the number of tutorials attended in the first 9 weeks (*tut_b8*), the logarithm of the number of Canvas pages viewed during the whole semester (*lpage*), student gender (*gender*) and whether the student missed the final exam (*miss*).

Data analysis

The results are presented in Table 5 and Figures 3 (Model 4) and 4 (Model 5). Results with those 7 observations omitted or replaced with 0 as robust tests are available upon request. Estimates of the three parametric models are presented in the second, third, and fourth columns of Table 5.

The results conform with our expectations. Students with stronger prior math skills perform significantly better in the unit: scoring one more point at the first online test on average increases the final exam score by about 0.24 points. Students who attend more tutorials obtain better scores too: attending one additional

tutorial in the first 9 weeks on average increases the final exam score by 2.4 points. Interestingly, female students on average perform better than males, scoring an average 8 additional points in the final exam.

All these differences are statistically significant. The coefficients for live lecture attendance in each of the three parametric models are statistically significant and indicate that students who attended the live final lecture scored about 9 more points in their final exam relative to students who did not come to the live lecture (and did not watch the recorded lecture either). Meanwhile, students who did not attend the live lecture would on average obtain 7 to 9 more points if they spent at least 100 minutes watching the recorded lecture (for Model 3, this result is reached within 78 minutes of watching the recording).

The three models give similar estimates for our iso-score rate of platform substitution (TRS_{LR}). For example, from the estimates of Equation (2), the most parsimonious model, we can derive that at the optimal level of effort, the average student values the 93 minutes-long live lecture at 127 minutes of watching its recording, which yields $TRS_{LR} = 1.4$. That model assumes this evaluation to be the same for every student.

When we allow for a quadratic relationship between exam scores and recorded lecture viewing time (Model 3), the estimate reduces to 99 minutes and $TRS_{LR} \sim 1$. However, the coefficient of the quadratic term is imprecisely estimated. Given the latter's large standard error, the two estimates may not be very different.

Table 5
Parameter estimates

	Model 2	Model 2'	Model 3	Model 5
Online1	0.236** (0.07)	0.239** (0.07)	0.240** (0.07)	1.000 (normalised)
cohort	-1.179 (4.37)	-1.107 (4.38)	-1.096 (4.36)	5.342 (5.89)
tut_b8	2.403** (0.76)	2.376** (0.76)	2.434** (0.58)	1.989 (1.42)
lpage	3.533 (2.86)	3.662 (2.87)	3.280 (2.86)	30.149** (6.09)
l13	8.973** (3.86)	9.952** (4.22)	9.272** (3.86)	15.055** (7.75)
vtime13	0.070** (0.02)	0.078** (0.03)	0.119** (0.05)	0.218** (0.06)
L13*vtime13		-0.030 (0.05)		
Vtime13-sq			0.0002 (0.0001)	
Gender	-7.896** (3.34)	-7.667** (3.37)	-8.657** (3.40)	-29.200** (5.55)
miss	-5.502 (7.27)	-5.345 (7.29)	-5.631 (7.26)	-46.765
cons	-9.528 (18.70)	-10.863 (18.89)	-8.817 (18.68)	
TRS	127.320 (63.63)	128.202 (58.08)	98.979 [§] (48.02)	68.909 (32.85)
Adjusted R-sq	0.417	0.419	0.419	

Note. $N = 129$. Standard errors are shown in brackets. *10% significant. **5% significant. [§]For Equation 5, TRS is calculated at the average viewing time (of the recording).

We also estimated the two semi-parametric models (Models 4 and 5). The results are presented in the last column of Table 5 and in Figures 3 and 4. For Model 4, the relevant parameters are not constant or of a known function, so they cannot be summarised and presented in the same way as the other models. Instead, they are summarised in Figure 3, which shows clearly that the relationship between test scores and the time spent watching lecture recordings is non-linear. The other parameter estimates are omitted as they are not the focus of the discussion. The estimates are in line with the parametric models with one exception: they report an apparently nonlinear impact of recorded lecture viewing time on the exam score. With a limited sample size of 129 observations the estimates are not precise enough and we will have to confirm this finding in further research.

These estimates are consistent with students' own perceptions reported in the in-class survey. Of the 129 students enrolled in QMC, 63 participated in the survey. Table 6 presents students' answers to two key survey questions: reporting the average time spent watching recorded lectures and the estimated watching time needed to achieve the same learning outcome as attending live lectures.

The first row of the table shows that the average reported duration watching the recorded lectures was about 84 minutes. In the second row we can observe that on average, students believe they need to spend 122 minutes of watching time in order to achieve the same learning outcomes as attending a live lecture would.

Table 6
 Survey responses: time spent watching recording and TRS live and recorded lectures

Survey question	N observations	Mean (std dev)	Range
Average length of time spent watching each recorded lecture	52	83.673 (40.09)	(0–135)
Time needed watching the recording for same learning outcome as attending live lecture	52	122.327 (78.21)	(60–600)

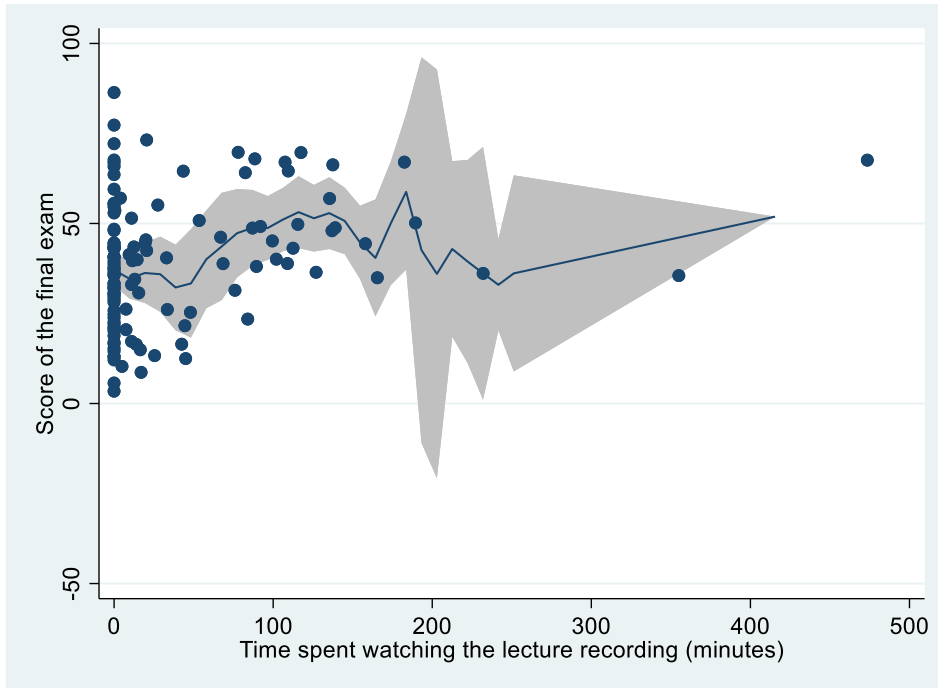


Figure 3. Estimated relationship between exam scores and time spent watching the recorded lecture from partial linear model (Model 4 with 95% confidence bands)

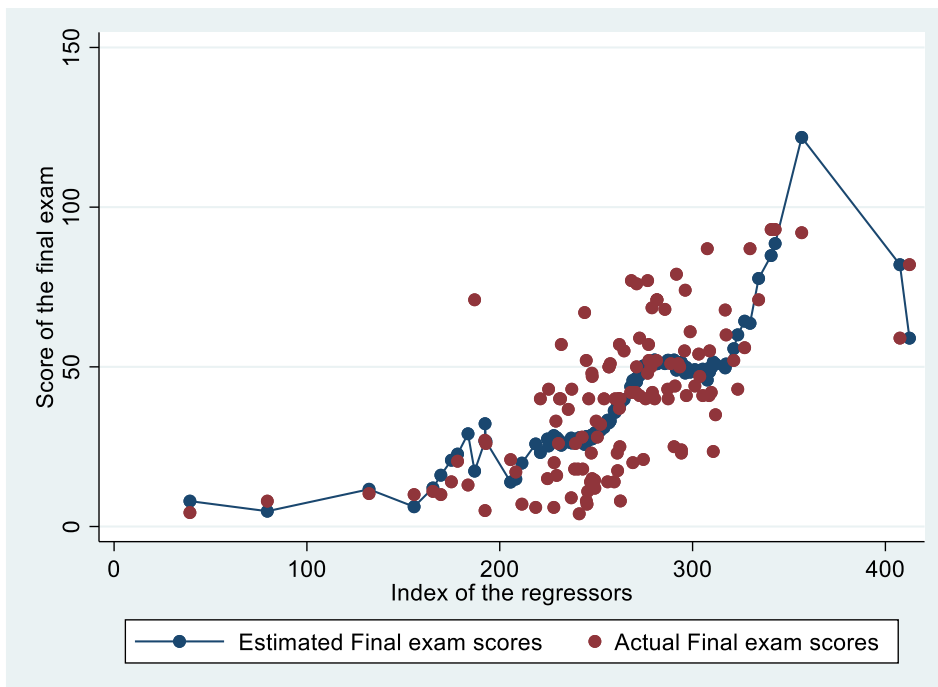


Figure 4. Estimated and actual scores as a function of estimated regressor index (Model 5: single index)

Discussion

Our study contributes to a fragmented and inconclusive field of empirical research in several ways. First, we provide estimates of the negative attendance and performance effects of using LCT in a core first-year quantitative business unit. Our results conform with expectations: not attending a lecture (nor viewing its recording) significantly predicts lower scores whereas higher prior math skills significantly predict higher scores at this quantitative course's final examination, as does regular attendance at tutorials. We also find significant gender effects.

More importantly, we made the case for using a measure of input substitutability, the TRS_{LR} —the technical rate of platform substitution. This parameter tells us how costly (time intensive) a teaching platform is relative to another platform for students to achieve a specific score. We find that non-attendance lowers scores but viewing about 127 minutes of recorded lecture makes up for it. Since the corresponding live lecture lasted a little over one hour and a half, the TRS_{LR} for our cohort of QMC students is about 1.4 (and conversely, $TRS_{RL} = 0.7$).

What is the interpretation of this parameter and what are the implications for research in this field? When the value of the TRS_{LR} equals (or nears) unity the two platforms are perfectly substitutable and there is input equivalence between live lecture attendance and corresponding lecture recordings. This implies that both platforms require similar time commitments to develop effective learning and achieve the highest possible scores. When the TRS_{LR} significantly exceeds unity the two platforms remain perfectly substitutable (linearly related) but lecture attendance is more score-efficient (i.e., more productive than lecture recordings for producing scores). For instance, $TRS_{LR} = 2$ implies that missing a two-hour lecture would require four hours viewing recordings to produce the same exam score. Lecture attendance is in that case a less time-intensive technology of producing exam scores and therefore a more cost-effective learning platform than its recording. This knowledge would presumably have a positive effect on lecture attendance. Conversely, when the TRS_{LR} is significantly less than 1, the traditional lecture is a less time-effective way of learning and achieving optimal scores.

At one extreme $TRS_{LR} \sim 0$ suggests that lecture attendance is sterile for generating exam scores and is best avoided. There is also the possibility that the traditional lecture and its recording are perfect complements (Bettinger et al., 2017) and must be used in fixed proportions, that is, they are not substitutable. In this case, no value exists for TRS_{LR} since no substitution of the two platforms could keep scores steady. Attendance is in that case very important for scores, as is supplementing lecture attendance with viewing recordings.

Our finding of $TRS_{LR} > 1$ aligns with those researchers who find negative effects of LCT on student performance, for example, McNulty et al. (2009), Xu and Jaggars (2013) and Edwards and Clinton (2019), and with those, such as Bennett et al. (2007), who find that students perform better in traditional delivery when the unit's contents are more quantitative. We do not want to attribute more weight to our estimates than our pilot project can realistically support, other studies have covered much more extensive ground. Our main contribution is to present the usefulness of our method and its central parameter, the TRS, as an easily replicable metric linking performance and attendance effects through consideration of the relative cost, productivity and interchangeability of each platform. Widely replicated, this metric would enable comparisons of findings on the performance effects of TEL platforms through a single, unit-free measure.

Our empirical approach could suffer from remaining identification issues. We control for unobservable characteristics by using students' initial screening scores in basic mathematics and statistics skills as a proxy for their ability, reasoning that such skills are arguably the most important ones to succeed in a quantitative course. But our analysis may be vulnerable to the omitted variable problem. That is, there may be other relevant factors that we have not accounted for, such as student learning styles or learning motivations that affect how efficiently students learn in each mode of lecture delivery (Fendler et al., 2016). If that is the case, such factors would almost certainly be correlated to scores, lecture attendance and time spent using recorded lectures. If omitted variables differ significantly across individuals our empirical approach would be weakened by unobserved characteristics. We plan to measure students' learning styles in the next iteration of this research.

A second set of limitations arises from the theoretical foundations our model derives from. We assume students act rationally, or at the very least that they have clear goals, understand their own limitations and try to minimise the time needed to achieve these goals. A rational student should be keen to evaluate whether a traditional or recorded lecture is the best suited resource to learn and perform at exams. Are we overstepping in expecting students to behave so efficiently? Fendler et al. (2018) for instance, show that students split between traditional and online delivery classes are not particularly apt at identifying the mode of delivery most likely to help them maximise their scores. Yet, over the run of several semesters (or an entire degree) we should expect students to eventually learn which teaching mode works best for them – if only by learning from their successes and failures. It should therefore not be an overly restrictive condition placed on student behaviour to expect them to identify and use the platform best suited to pursuing that strategy.

There are also in-built limitations in the revealed preference approach (i.e., observed behaviour) we adopted. We only capture one observation for each individual student. We do not observe the entire locus of traditional and recorded lectures combinations that could enable students to attain their targeted scores. Although our observed outcomes suggest imperfect substitution between attendance and recordings it is possible that other types of behaviour could produce the same results.

Recommendations

- Measures of learning platform substitutability should be used to learn about students' effective use of online learning technologies.
- Estimating measures of learning platform substitutability should help select the right mix of online and offline delivery methods.
- Researchers studying the relative effectiveness of online and offline learning technologies should consider using the method proposed in this study to compare and generalise results from existing studies.

Conclusions

Research into the effects of LCT on student behaviour and attainment has produced valuable but divergent, context- or cohort-dependent, methodologically unaligned and contested results. Recent reviews have highlighted the difficulties of generalising these results in light of the complexity of learning and teaching processes (Banerjee, 2021; Nordmann et al., 2020; O'Callaghan et al., 2017). Yet, as has been stressed by many, consolidation of this knowledge is necessary to take stock of what works in TEL environments and to inform further deployments of technology in teaching and learning practice.

In this study, we proposed a procedure centred on estimating a single parameter, the TRS. The TRS is designed to facilitate comparison and generalisation of empirical results. Analysing the results from a quantitative methods course in which student time was monitored, we presented how to derive this parameter and interpret its meaning.

In the context of our study, our parameter estimates suggest imperfect substitution between attendance and recording as learning platforms used to perform at examinations. A lecture recording requires significantly more time and effort than lecture attendance to produce the same score. Our results were also supported by an end-of-term survey asking students about their LCT-assisted experience.

In future work, we plan to apply the procedure to a set of pre-existing studies to illustrate the potential for generalising our method. We will also consider developing a web calculator. An easily computable TRS metric could inform policy about teaching delivery post-pandemic (recording vs. on site lectures) and guide instructors within-course choices about the most appropriate platform to deliver different types of content (e.g., substantive vs. revision lectures). Finally, we plan to further explore the determinants of the TRS by collecting more data about the learning styles and motivations of our students.

Ethics statement

This research project received ethical clearance (#4634 from the University of Canberra's Human Research Ethics Low Risk Panel and follows the Australian Government's National Statement on Ethical Conduct in Human Research. All data used in this study was systematically de-identified to ensure the confidentiality and privacy of its participants. Access to the de-identified data used in this study will be considered upon request.

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