6-2019

Are e-learning tools actually useful? Assessing the effect of online learning resources on student outcomes

Hisham PATEL

Swee Liang TAN

Are e-learning tools actually useful? Assessing the effect of online learning resources on student outcomes.*

Hisham Yacob Patel, Tan Swee Liang
Singapore Management University

Abstract

This paper tests to see if the usage of online learning resources affects student outcome, in an Economics of Globalisation course, taught over 2 consecutive terms. Outcome is measured by overall score obtained in the final examination. We adopted two different measures of the usage of online learning resources; partial participation, and full participation. The results show that partial participation does not improve final score while full participation improves final score by 6.4 marks (out of 100). The results also show that the overall score improvements are largely driven by score improvement in the essay component of the final examination, as opposed to the Multiple-Choice Question (MCQ) component of the examination.

I. Introduction

With the advent of technology, there has been a push towards incorporating online material in schools across Singapore. This push is also motivated by the vein of accessibility; to grant willing and able students access to education, regardless of circumstance. One popular method of incorporating online material into the curriculum is through the delegation of a portion of the material to e-learning websites. Most university-level Economics textbooks come with an online component, with numerous exercises and activities that are available to both instructors and students to help provide a holistic learning environment. The current consensus is that incorporating such tools will help improve student learning since the newer generation are more acclimated to the use of technology. In this paper, we are interested in extracting the latent effect of online learning resources on student outcomes, alongside disentangling the effect of different levels of participation in the online platform.

We conducted a pedagogical experiment in a traditional classroom setting. The course is a seminar-format undergraduate *Economics of Globalisation* course in a four-year public

*Corresponding author: Hisham Yacob Patel, Singapore Management University. Email: hishamyp.2018@smu.edu.sg

We thank Ani Aghababyan from McGraw-Hill Education & Ryan Baker, as well as seminar participants at the Canada International Conference for Education (CICE) 2019 for their helpful comments. We thank Magdeleine Lew Duan Ning & Yvonne Tan Yi Wen for providing valuable inputs to the earlier versions of this paper.

university in Singapore. 40-45 students are typically enrolled in a class, with multiple classes offered for most courses. The experiment is conducted over two consecutive batches of student – 75 student-participants in the Spring '18 cohort, and 39 student-participants in the Fall '18 cohort. Students can earn by to 5% of the total course grade by fully completing all the prescribed *LearnSmart* components of the online learning platform. Participation in the study is on a voluntary-basis, and all student-participants are required to fill in a survey at the start of the course. The reference textbook used for the course is *International Economics* (16th Edition) by *Pugel*, with the accompanying online platform, *McGraw-Hill Connect*.

II. Literature Review

A similar experiment was conducted by Trost and Salehi-Isfahani (2010). The authors examined the effect of completing the online homework assignments on examination performance in the *Principles of Economics* course. One key difference is that the authors randomised students into two groups, those for whom the assignment was optional and those for whom it was mandatory. They used this as an instrument to help identify the effect of homework completion on topic-specific examination performance. They found the completion of the homework assignment to be positively correlated with higher scores on the mid-term examination, but not on the final examination; indicating a *decaying* effect of doing the homework over the course of the term.

A considerable amount of literature currently exists on the importance of online learning on overall student success. For example, Lass, et al (2007) found that online quizzes have a significant positive effect on final examination scores while Emerson and Mencken (2009) found that graded online homework have a positive effect on final examination performance, as well as course grades. Furthermore, Dahlgran (2008) found that online homework increases learning through increased student study-time allocations. Most importantly, Agarwal and Day (1998) found that internet use positively affects both Testing of Understanding College Economics III (TUCE), as well as final grades in introductory economics. In contrast, Rankin and Hoass (2001) found that computer-assisted instruction does not improve student performance. They also found no effect on student attitudes and teaching evaluations.

Similarly, a consensus has also not yet been reached when it comes to comparing the impact of online learning tools by gender. Brown and Liedholm (2002) found that females performed slightly better in the online setting while Sosin, et al (2004) found that women performed worse than men in economics classes.

Our paper contributes to the existing literature in two dimensions. First, we add to the existing literature on the short-term effects of e-learning on student outcomes. Secondly, to the best of our knowledge, our paper is among the first attempts to assess the differing effects of partial vs full participation in the online platform.

The rest of the paper is organised as follows: the data collection process is described in the next section, followed by our empirical models and results obtained. We then finish with further analyses and robustness checks, before concluding.

III. Data

The data used in this paper was collected during two terms: Spring 2018 and Fall 2018, in an undergraduate *Economics of Globalisation* course. This is a 12-week course, with sections taught by the same instructor. Each cohort of students is divided into different sections, consisting of 40-50 students each. The same instructor taught all the sections during the period of this study. Most of the students in the course were Business majors – 79% – who were taking the class to fulfil the Globalisation elective requirement of their major.

Participation in the study is completely voluntary and do not factor into the course assessment. All student-participants are surveyed at the start of the term to collect demographic information. As students are required to provide informed consent to participate in the study, the total sample size was 114, out of a total cohort size of nearly 400 students. Key demographic details are presented below, in Table 1.

	N	Mean	St.Dev	Min	Max
Major					
Business	114	.789	.409	0	1
Economics	114	.132	.34	0	1
Double Degree Programme	114	.009	.094	0	1
Social Science	114	.018	.132	0	1
Information System	114	.035	.185	0	1
Accounting	114	.018	.132	0	1
Year 1	114	.105	.308	0	1
Year 2	114	.553	.499	0	1
Year 3	114	.281	.451	0	1
Year 4	114	.061	.241	0	1
AY2018/19 Cohort	114	0.342	0.477	0	1
Male	114	.456	.5	0	1

Table 1. Descriptive Statistics for Demographic Variables

Major-of-study dummy variables are included to help overcome potential self-selection issues. For example, students who major in Economics might be more equipped to score better in the course, as compared to students with other majors as they can leverage on knowledge obtained from other Economics courses. Furthermore, we also wish to see if students from certain majors systematically perform better than students with different majors who take this course as an elective.

Year-of-study dummy variables are included to help isolate any academic maturity as a result of a longer time spent in higher education; *Year 1* takes the value 1 if a student is a freshman, 0 otherwise; *Year 2* takes the value 1 if a student is a sophomore, 0 otherwise; *Year 3* takes the value 1 if a student is a junior, 0 otherwise; *Year 4* takes the value 1 if a student is a senior, 0 otherwise. We omit *Year 4* in all our specifications to avoid multicollinearity. We also include a dummy variable that takes the value 1 for students belonging to AY2018/19 (students from the Fall '18 cohort), 0 otherwise. While the course is being taught by the same instructor, using the same material, the cohort dummy variable aims to capture differences that might exist between cohorts; differences like the difficulty of the final examination paper, as well as minute differences in the instruction of the course that might vary with each cohort of students, but commonly affects all students in the same cohort.

The dependent variable chosen is the final examination score. The final examination score is derived from a weighted sum of the score obtained in the Multiple-Choice Question (MCQ) section and the score obtained in the written essay component. The variable of interest is the usage of the online learning resource. We employ two different measures of the usage of the *LearnSmart* online learning platform; partial participation, and full participation. Both variables are binary in nature, with the former taking the value 1 if a student uses any component of LearnSmart, 0 otherwise, and the latter taking the value 1 if a student completes all components of LearnSmart, 0 otherwise. Table 2 presents descriptive statistics for the outcome variables used in the paper.

	N	Mean	St.Dev	Min	Max
MCQ Section	114	77.334	12.712	44	100
Essay Section	114	68.612	14.913	13.85	96.92
Overall Final Score	114	70.695	12.228	36.923	96.25

Table 2. Descriptive Statistics for Outcome Variables

The average score obtained in the MCQ component of the final examination is 77% while the average score obtained in the essay component is 69%. The average combined score in the final examination is 70%.

In addition to the demographic markers presented in Table 1 above, we also have additional information on the lecture groups that each individual belongs to, as well as information on whether or not a student has had prior experience with e-learning in the past. The reason for the inclusion for this variable as familiarity with the notion of online learning might be correlated with the likelihood of fully participating in the prescribed e-learning components. 42% of students in the sample reported having had prior experience using e-learning resources.

IV. Empirical Model & Results

We begin by regressing our dependent variables on partial participation and full participation alone. We then systematically expand our model by increasing our number of controls to test for the robustness of the results, as well as to see if the results are getting biased due to collinearity between explanatory variables. Our largest specification employed a class fixed effects model, after controlling for student characteristics.

A class fixed effects model was employed for 2 main reasons. Firstly, class participation accounts for 5% of the total course grade. Students can obtain class participation points by posing questions to the instructor during lessons or provide meaningful insights to the material being covered in class. This assessment component therefore introduces some variability to the *actual* content covered in different classes, as a student might raise a particular query in one class that might improve the understanding for students who were present for that lesson.

Secondly, a group project constitutes another significant portion of the course assessment. Students are made known of this feature of the course, and are allowed to freely select their group members. Therefore, students can coordinate with their peers and enrol in the same class section when enrolling into the course. Therefore, such a phenomenon might affect an individual's learning experience, as well as the overall classroom dynamic, which can be captured by a class fixed effects model. Our presented model estimates the effect of participating in the online learning platform, using the following specification:

$$Score_{ijk} = \alpha_1 \cdot Partial\ Participation_{ijk} + \alpha_2 \cdot Full\ Participation_{ijk} + \boldsymbol{\delta X}_{ij} + \mu_j + \varepsilon_{ijk}$$

Where $Score_{ijk}$ is the test score of the i^{th} student, in the j^{th} class, in the k^{th} subject – k = MCQ, essay or total –, and the coefficient α_1 & α_2 capture the effect of partial and full participation in the online learning platform. The vector X corresponds to the individual characteristics of the i^{th} student, in the j^{th} class, while μ_j represents the class fixed effects. ε_{ijk} represent the remaining unobserved error term.

Referencing Table 3a, the first variable of interest, partial participation, remains statistically insignificant across all our specifications, regardless of the outcome variable of choice. This suggests that partial participation in the online learning platform yields little benefit in promoting understanding and improving grades. However, it is important to note that there exists little variation in the variable, with 97% of all students participating in some aspect of the platform, which could potentially mask some of the effect of partial participation on the final examination score.

	Outcome Variables					
	MCQ	Essay	Total	MCQ	Essay	Total
Partial Participation	-0.0900	-6.067	-5.110	5.031	0.229	0.0292
	(6.91)	(6.18)	(4.80)	(5.59)	(6.78)	(5.44)
Full Participation	5.676*	7.228**	6.399**	4.238	7.120**	6.361**
	(2.97)	(3.61)	(3.04)	(3.30)	(3.22)	(2.77)
Controls						
Individual Characteristics				✓	✓	✓
Class Fixed Effects				✓	✓	✓
N	114	114	114	114	114	114
R^2	0.032	0.034	0.040	0.392	0.229	0.278

Note: Robust standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 3a. Regression Estimates for both partial and full participation in the e-learning platform

Our second variable of interest, full participation, remains statistically significant across most of our specifications, at the 5% level; more specifically, those with *Essay* and *Overall Score* as dependent variables. Full participation in the e-learning platform is associated with a modest 7.1 and 6.4 marks increase in the Essay and Overall Score respectively. In addition, the point estimates consistently reduce in magnitude when controls are added.

However, there is exists one limitation of our current research design; the completion of all elements of *LearnSmart* is a graded component in the course. Therefore, the full participation variable could simply be capturing the conscientiousness attribute of students, and not the latent effect e-learning has on student outcomes, as students will be inclined to simply complete the online components to secure the grade. Conscientious students will be more driven to complete all components of *LearnSmart* and this conscientiousness attribute also translates to diligence in revision, which will result in a better course grade. Lundberg (2013) did, in fact, find empirical evidence that conscientiousness is the key driver of school success.

Notwithstanding, full participation in the online learning platform provides a score improvement of approximately 6.4 marks to the total final grade, even after adding numerous controls. Delving deeper, we notice that this score improvement is predominantly driven by improvements in the essay component of the final examination, with full participation providing a score improvement of 7.1 marks in the essay section of the examination, after adding all controls. All in all, full participation in the online platform effectively bumps a student's score up by a minimum of 1 grade, and a maximum of 2 (i.e. from a B- to a B or a B+).

With regards to other findings – not present in our truncated table, but available upon request –, contrary to our initial hypothesis, we did not find any evidence that Economics majors were doing better than their peers. In fact, the students enrolled in the Double Degree programme (DDP) are observed to score higher by a considerable margin – 33 marks, in fact – and that the difference is statistically significant at the 5% level. This is to be expected, especially admission into the DDP is difficult, and thus, the score differential could potentially be due to them being high ability students, in a broad sense. With regards to year-of-study, we did not find any statistically significant differences. Turning our attention to the classroom identifiers, we notice that there are statistically significant differences in certain classes. For example, students in the G11 section of the Spring '18 cohort, on average, perform at least 13 marks higher than their peers in the Spring '18 cohort, with the difference being statistically significant even at the 5% level. Therefore, this confirms our belief that some differences exist across different classes, and that it is prudent to employ a class fixed effects model.

Gender Interactions

Next, we explored if gender had any role to play in the effectiveness (as well as receptiveness) of the e-learning platform. To that end, we observe that 85% of male students fully complete all the prescribed elements of LearnSmart, vs 75% for female students. However, females have a higher partial participation rate, at 98.4% vs the participation rate of 96% for male students. Therefore, we included gender interaction terms into our regression estimates, and present our findings below, in Table 3b.

We observe that the inclusion of the gender interaction terms does little to materially alter the coefficient estimates when essay and total scores were the chosen outcome variable. However, when MCQ score were the outcome variable of choice, the coefficient estimates for full participation turns statistically insignificant, while the counterpart for partial participation now becomes significant at the 5% level. Furthermore, the gender interaction terms were all statistically insignificant except when MCQ were the chosen outcome variable. Interestingly, the gender interaction terms for partial and full participation are of the opposite signs; negative for partial participation, and positive for full participation. We are unable to account for this anomaly found here.

	Outcome Variable		
	MCQ	Essay	Total
Partial Participation	18.34***	-0.465	3.195
	(4.65)	(4.41)	(4.01)
Full Participation	0.723	8.141**	6.461*
	(3.96)	(3.85)	(3.30)
Male	22.68***	0.580	6.865
	(3.43)	(9.80)	(7.39)
Male x Partial Participation	-24.14***	2.210	-4.678
	(6.15)	(11.6)	(9.26)
Male x Full Participation	10.26**	-3.041	-0.360
	(4.99)	(6.98)	(5.63)
N	114	114	114
R^2	0.420	0.230	0.279

Note: Robust standard errors in parentheses
$^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Table 3b. Regression estimates with gender interaction terms

V. Sensitivity Analysis

Conscientiousness

As previously noted, we believe the conscientiousness attribute affects the likelihood that a student completes all elements in *LearnSmart*. Thus, our estimates obtained above could also be encapsulating a multitude of student characteristic that contribute to better performance in the final examination. In a bid to extract the latent effect of e-learning on student outcomes, we repeat the above analyses on a restricted subsample. First, we sort students based on their score obtained in the mid-term examination. Drawing from Lundberg (2013), we believe that conscientiousness is a common trait shared between high achievers, and thus we chose to omit the top 10% of students based on their midterm scores, in a bid to remove the trait from our analysis. We are then left with 104 observations in our subsample. We replicate the specifications presented in the previous section using the restricted subsample. The results are shown in Table 4, accompanied by the original point estimates from Table 3, for ease of comparability.

	Outcome Variable					
	MCQ	MCQ	Essay	Essay	Total	Total
Partial Participation	5.031	4.949	0.229	0.293	0.0292	0.0782
	(5.59)	(5.39)	(6.78)	(6.40)	(5.44)	(5.32)
Full Participation	4.238	5.667	7.120**	5.635	6.361**	5.661*
	(3.30)	(3.88)	(3.22)	(3.57)	(2.77)	(3.14)
Controls						
Individual Characteristics	✓	✓	✓	✓	✓	✓
Class Fixed Effect	✓	✓	✓	✓	✓	✓
Conscientiousness		✓		✓		✓
N	114	104	114	104	114	104
R^2	0.392	0.416	0.229	0.251	0.278	0.304

Note: Robust standard errors in parentheses
$^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Table 4. Regression Estimates after omitting top 10% of students

As before, partial participation in the online learning platform continues to yield statistically insignificant coefficient estimates, at the 10% level. Turning our attention to full participation, we note that the coefficient estimates become statistically insignificant when essay scores were the outcome variable of choice. This seems to suggest that the effect captured by the full participation variable appears to also be capturing the effects of positive attitudes that are common across the top performers in class. Notwithstanding, the coefficient estimates for full participation remains statistically significant at the 10% level, albeit with a smaller magnitude, after controlling for conscientiousness. Therefore, we can safely conclude that our findings are somewhat robust to the idea of conscientiousness.

In addition, our subsample findings are robust to the % cut-off used to classify conscientious students. We found similar and persistent effects at various cut-offs, with the statistically significant effect of full participation only disappearing once we remove more than 25% of observations.

Alternative Specification

In this next sub-section, we explored the robustness of our findings to alternative specifications. To that end, we generated 3 separate dummy variables corresponding to the relevant grade thresholds for B-, B & B+. These dummy variables individually take the value 1 if a student scores at least a B-, B or B+, respectively, and zero otherwise. We report the coefficient estimates when using these 3 variables as outcome variables, in Table 5 below.

	Outcome Variable		
	B-	B	B+
Partial Participation	0.243	0.221	0.178
	(0.32)	(0.28)	(0.13)
Full Participation	0.251**	0.177*	0.156*
	(0.11)	(0.11)	(0.079)
Controls			
Individual Characteristics	✓	✓	✓
Class Fixed Effect	✓	✓	✓
N	114	114	114
R^2	0.253	0.273	0.195

Note: Robust standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5. Regression Estimates under Alternative Specifications

Referencing Table 5, we observe that partial participation yielded statistically insignificant results, as previously noted throughout the paper. The coefficient estimates for full participation, however, are consistently statistically significant at the 10% level. This means that conditional on all other included parameters, fully participating in the e-learning platform increases a student's likelihood of getting at least a B- by 25%. We note that the magnitude decreases as the relevant threshold gets higher, suggesting that the online learning platform is most effective in helping the median students, and not students who are actively aiming to get As & A^{+}'s. This seems plausible, given that the e-learning platform aims to reinforce the instruction of the material during lessons, and recap certain key ideas. For the more gifted students, such a recap might be less meaningful as they might have fully grasped the content from the get-go. Nonetheless, the results presented here further suggests that our findings are robust to alternative specifications.

Frequency Weights

Owing to the nature of how data was collected in this study – student participation is on a voluntary basis –, some classes are invariably overrepresented in the sample as certain classes might yield more volunteers than others. In order to reduce any propagation of classroom effects in our resultant point estimates, we also employed the use of frequency weights, in order to give observations from each class equivalent weights, on a class level. We present the results in Table 6, along with the original point estimates, for ease of comparability.

	Outcome Variable					
	MCQ	MCQ	Essay	Essay	Total	Total
Partial Participation	5.031	5.508**	0.229	6.843**	0.0292	5.326**
	(5.59)	(2.69)	(6.78)	(3.47)	(5.44)	(2.54)
Full Participation	4.238	3.750**	7.120**	4.815***	6.361**	3.906**
	(3.30)	(1.86)	(3.22)	(1.72)	(2.77)	(1.53)
Controls						
Individual Characteristics	✓	✓	✓	✓	✓	✓
Class Fixed Effects	✓	✓	✓	✓	✓	✓
Frequency Weights		✓		✓		✓
N	114	301	114	301	114	301
R^2	0.392	0.463	0.229	0.372	0.278	0.404

Note: Robust standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6. Regression Estimates with Frequency Weights

Referencing Table 6, we observe that the coefficient of full participation, which still statistically significant at the 5% level, decreases in magnitude across all specifications, regardless of the outcome variable of choice, when frequency weights were incorporated. This suggests that our original results might be partly driven by class-specific confounders. In addition, interestingly, the coefficient estimates for partial participation consistently increases in magnitude, and is now observed to be statistically significant at the 5% level. Notwithstanding, the findings presented in this section suggests that our findings are robust to the use of frequency weights.

VI. Conclusion

Results from our full sample agree with Harter and Harter (2004), in that online learning resources did not improve students' scores in the MCQ component of the examination. In addition, our findings coincide with Sosin, at al (2004), in that males consistently perform better than females, in the MCQ component of the final examination, both in the full sample, as well as the restricted subsample. One possible explanation for the gender differences is that local males in Singapore enter university 2 years later than their female counterparts, due to mandatory National Service[2]. Dhuey, et al (2017) found that older students perform better than their younger counterparts due to maturity differences. While their paper focused on students aged 6 – 15, we believe a similar phenomenon exists in university students as most matriculating students are on the cusp of adulthood. The additional time spent before matriculation might help realign objectives and priorities, before starting higher education.

Our findings contribute to the vast literature that currently exists on the effectiveness of online learning. We are also amongst the first to disentangle full participation and partial participation in the online medium; an avenue that was previously missing in existing literature.

In conclusion, we present two central takeaways from the findings of our paper. Firstly, as noted in previous sections, partial participation in the online learning platform yields no statistically significant improvement in final examination scores, while full participation rewards students with a modest improvement of 6 marks in their overall final score. This suggests that more effort should be employed by course instructors to ensure that students not only participate in the online learning platform but complete all the elements prescribed by the course. Secondly – and arguably the more practical application – course instructors can leverage on our findings to justify an increase in funding from the university for such e-learning packages.

[2] National Service in Singapore is a statutory requirement for all male Singapore citizens, as well as second-generation permanent residents. The length of service is either 22 or 24 months, depending on individual fitness level. All eligible males are required by law to complete their service obligations prior to starting university.

References

R. Agarwal, A.E. Day, 1998. “The impact of the internet on economic education”, *Journal of Economic Education*, 29(2), pp. 99–110.

B.W. Brown, C.E. Liedholm, 2002. “Can web courses replace the classroom in principles of microeconomics?” *American Economic Review,* 92(2), pp. 444–448.

R. Dahlgran, 2008. “Online homework for agricultural economics instruction: Frankenstein’s monster or Robo TA?” *Journal of Agricultural and Applied Economics,* 40, pp. 105–116.

E. Dhuey, D. Figlio, K. Karbownik, J. Roth, 2017, “School starting age and cognitive development”, *NBER Working Paper 23660*

T.L.N. Emerson, K.D. Mencken, 2011. “Homework: To Require or Not? Online Graded Homework and Student Achievement”, *Perspectives on Economic Education Research*, Vol. 7, No. 1

C.L. Harter, J.F.R. Harter, 2004. “Teaching with technology: does access to computer technology increase student achievement?” *Eastern Economic Journal*, 30(4), pp. 507–514.

D. Lass, B. Morzuch, R. Rogers, 2007, “Teaching with Technology to Engage Students and Enhance Learning.” University of Massachusetts-Amherst, *Department of Resource Economics Working paper no. 2007-1.*

E. L. Rankin, D. J. Hoaas, 2001, “Does the Use of Computer-Generated Slide Presentations m the Classroom Affect Student Performance and Interest?” *Eastern Economic Journal*, Summer 2001, pp. 355-66

S. Lundberg, "The College Type: Personality and Educational Inequality," *Journal of Labor Economics*, 31, no. 3 (July 2013), pp. 421-441.

K. Sosin, B. Blecha, R. Agarwal, R. Bartlett, J. Daniel, 2004. “Efficiency in the Use of Technology in Economic Education: Some Preliminary Results.” *American Economic Review*, 94(2), pp. 253–258

S. Trost, D. Salehi-Isfahani, 2010. “Assessing the effect of online homework on exam performance: a large sample size experiment”, paper presented at the *American Economic Association Annual Meetings*