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The benefit of providing face-to-face lectures in online learning microeconomics courses: Evidence from a regression discontinuity design experiment

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Abstract

This paper explores the effect of attending face-to-face lectures on examination performance in online Intermediate Microeconomics courses using a regression discontinuity experimental approach. The instructor implemented a policy requiring students who scored below the class mean on the first exam to attend four face-to-face lectures before the second exam. The estimation results show that, on the average, attending face-to-face lectures does not improve online learning students' examination performance. However, for the group of students who did not or chose not to access online course materials, attending face-to-face lectures did produce a significant and positive effect on their grades. As revealed from this study, offering face-to-face lecture options to online learning students requires more resources but does not significantly improve students' examination performance. In order to enhance students learning particular for low performing students, a cost effective policy option might not be requiring students to attend face-to-face lectures but discovering ways to encourage or require students accessing pre-recorded lectures.

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1. Introduction

Presently, online learning and web-enhanced instruction have become widespread in higher education. As a result of information technology advances and cost saving concerns, many universities and colleges have expanded their online learning programs in the last decade. Online learning opens educational opportunities to a larger variety of the population, such as working adults and students with special needs. With the availability of online learning programs, students are able to access college education and learn diverse subjects anywhere or any time. In addition to online programs, many professors have adopted web-based enhancements such as online recorded materials, discussion boards, online quizzes and online office hours to supplement students learning in traditional classroom instruction.

As the online learning programs become prevalent in college education, it is important to pay special attention to the quality of online education and investigate whether or not students perform significantly different under various types of instruction. Online learning not only provides a flexible channel through which students can learn and access course materials regardless of locations and time, but also improves traditional distance instruction by allowing students to communicate and collaborate with each other in a virtual classroom. However, there are some disadvantages associated with online learning programs such as the lack of face-to-face interactions with the instructor and peers, difficulties to adopt technology and the likelihood of developing procrastinating study habits.

A combined teaching style of using online media and traditional face-to-face interaction can be seen as a hybrid or blended instruction. A hybrid or blended course may produce beneficial effects for students' learning outcomes because students can access online materials frequently whenever and wherever they want and still have the opportunity to interact with instructors and peers in the real classroom. However, hybrid or blended courses may impose more workloads on both students and instructors and that may negatively affect learning outcomes (Vachris, 1999; Reasons, 2004).

Many researchers use control experiments to investigate the effectiveness of various teaching styles such as face-to-face teaching, online learning and blended instruction. Some existing studies fail to find significant differences in students' academic performance among different learning modes. One possible reason for the insignificant effects might be a result of students' heterogeneous response to different learning modes. For instance, some students might be better fit for online learning, and others might benefit the most from face-to-face lectures. Therefore, it is possible that the average treatment effect becomes insignificant because of the heterogeneous outcomes.

The main purpose of this paper is to examine whether or not attending face-to-face lectures improves students' examination performance in an online learning Intermediate Microeconomics course. We are particularly interested in the group of online learning students who have poor examination performance in the early stage of a semester. If we find attending face-to-face lectures help students learn better, instructors may consider offering this extra resource to online learning students. Offering the choice of attending face-to-face lectures in an online learning program can be regarded as one type of hybrid teaching models. To evaluate the effects of face-to-face teaching on students' examination performance in the online learning course, a regression discontinuity design are conducted in this study to circumvent potential sample selection problems.

The organization of this paper is described below. The next section reviews literature; section 3 describes data and experimental design; section 4 outlines the statistical model; section 5 discusses empirical results, and section 6 presents the conclusions.

2. Literature Review

Whether or not information technology advances produce positive effects on students' learning outcomes has sparked great interest from researchers in many fields. Many efforts have been devoted to studying the pros and cons of online-related instruction and investigating examination performance of college students under different delivery of teaching styles. Some researchers found that web-based enhancements are effective tools to improve students' performance by encouraging their participation in the course through internet (Agarwal and Day, 1998; Flores and Savage, 2007; Sosin et al., 2009; Damianov et al., 2009; Calafiore and Damianov, 2011; Chen and Lin, 2012). However, other researchers did not find favorable results for online media on the learning outcomes in higher education (Savage, 2009).

As for the comparison of students' learning outcomes between online instruction and traditional instruction, some researchers demonstrated that students perform better in traditional face-to-face courses than in online courses (Brown and Liedholm, 2002; Figlio et al., 2013). Conversely, some researchers found that online students actually outperform their peers who attended face-to-face courses (Smith and Hardaker, 2000). Furthermore, some studies revealed that there is no significant difference in students' examination performance between face-to-face lecture instruction and online instruction (Russell, 1999; Batte et al. 2003; Coates et al., 2004).

In addition to fully online or fully traditional chalk-and-talk teaching styles, hybrid or blended teaching style is growing. Hybrid or blended courses combine two different styles of teaching and may preserve the benefits of both approaches (Collopy and Arnold, 2009). For instance, students can take advantage of internet advances without losing the interaction and collaboration with peers (Vernadakis et al., 2012). However, students may feel restricted to the rigid face-to-face meeting time and be confused by switching the teaching modes between online instruction and traditional instruction. Moreover, students and instructors may also need to make more efforts to meet each other's expectations in a hybrid setting (Reasons, 2004; Mansour and Mupinga, 2007).

With regard to the evaluation of hybrid teaching, studies conducted by different researchers reached different conclusions depending on methodology, sample size, and course subjects. As pointed out by Hachey et al. (2014) and Haverila (2011), students' previous online learning experience might be a major indicator toward their success in future online learning courses. Some students might learn better in online learning courses but some might need extra help. McVey (2009) found that the integration of online components into traditional teaching enhances learning outcomes; students in the hybrid teaching group scored better than the traditional classroom group in a research method course. Similar results were found in an undergraduate computer software course (Vernadakis et al., 2011). Many prior studies have shown that adding online features such as captured classroom lectures or supplemental online recorded lectures to traditional instruction enhances students' learning outcomes (Dey et al., 2009; Euzent et al., 2011; Chen and Lin, 2012). Kakish et al. (2012) compared students' examination performance between traditional class teaching and hybrid teaching in a statistics course. The authors, however, discovered that students' academic performances between these two groups are not significantly different from each other.

This paper studies from a different angle and explores whether or not offering face-to-face teaching to low-performing online learning students improves their examination performance. In this paper, same course materials, i.e. identical PowerPoint slides covered in the pre-recorded online program, were taught by the same instructor in the face-to-face classroom sessions. In addition to taking advantage of information technology advances provided by the online program, the face-to-face learning option offers students extra opportunities to learn and interact with the instructor and peers. Therefore, online learning students might benefit and learn better from this type of hybrid instruction, particularly for those poor-performing students. Additionally, this study adds value to the literature by using a unique data set and implementing a regression discontinuity method to identify the causal relationship between face-to-face lecture attendance and examination performance in a fully online economics course.

3. Data and Regression Discontinuity Design

This study used data from two online learning Intermediate Microeconomics courses. Two sample groups including 108 students in the Fall of 2011 and 109 students in the Fall of 2012 were included. The two online courses were taught by one of the authors at a public university in Taiwan. The university is among the top two of Taiwan universities in social science research. Most students enrolled in the online learning Intermediate Microeconomics courses were sophomores and majored in business. Each semester consisted of 17 weeks of instruction. 12 online pre-recorded lectures were assigned to 12 of the weeks, 3 examinations and 2 in-class project presentations were assigned for 5 of the weeks.

There were around 10 Intermediate Microeconomics courses offered at the university every semester, and only one of them offered online learning option during the sample period. Students could choose to enroll in any of the 10 Intermediate Microeconomics courses. It is of note that a potential selection problem may arise because students who chose to enroll in online courses instead of traditional face-to-face courses might be the ones who benefit the most from online learning. Therefore, estimation results derived from this study should be interpreted as for students who select to take online courses but not for the general student population at the university.

The instructor implemented a mandatory attendance policy which was stated on the course outline. The attendance requirement was contingent on students' first examination performance. The first exam was held at the sixth week in both semesters. There were 4 live in-class lectures offered after the first exam and before the second exam. If a student's first exam score was below the class mean, he or she would be required to attend the subsequent four lectures taught by the instructor. Since students did not know the exact mean grade when preparing for the first exam, whether or not students were required to attend live lectures can be assumed to be random around the cutoff point, i.e. the mean score. Additionally, there was no punishment if students missed any of these required lectures. As for students with above mean grades, they were free to choose whether to attend live lectures or not.

In these four face-to-face lectures, identical PowerPoint slides covered in the pre-recorded lectures were taught by the same instructor. The group of students who scored just below the class mean on the first exam was regarded as the treatment group in the regression discontinuity analysis. The group of students who scored just above the class mean on the first exam was regarded as the control group. By comparing the second exam performance of the treatment group with the control group, we were able to estimate the face-to-face lecture attendance effect for students whose first exam grades near the class mean.

Even though students who scored below the class mean were required to attend the four face-to-face lectures before taking the second exam, some students were still absent. On the average, students in the treatment group attended 3 lectures. Because not all the students in the treatment group attended all 4 lectures in this quasi experiment, the study was considered as a fuzzy regression discontinuity design in the literature.

4. Statistical Models

Equation (1) describes the relationship between a student's examination performance and a range of learning inputs.

$$y_{ij} = \eta r_{ij} + x_{ij}\beta + \gamma_j + \varepsilon_{ij}, \qquad i = 1, 2, \ldots, I, j = 1, 2, 3, \ldots, J \tag{1}$$

y_{ij} corresponds to student i's observed examination performance on question j, which is defined as percentage of the score awarded for question j. r_{ij} is the *attendance* variable which is equal to 1 if student i attends the corresponding face-to-face lectures when question j is covered; r_{ij} is equal to

0 if student i does not attend face-to-face lectures when question j is covered. The coefficient η, which is the major interest of this paper, represents the face-to-face lecture attendance effect on examination scores. x_{ij} is a vector of covariables which affect a student's exam performance. γ_j represents question j's specific effect, and ε_{ij} is a random disturbance term. I denotes total number of students; J denotes total number of examination questions.

There is a potential endogenous problem associated with the attendance variable if we use the ordinary least square method to estimate the attendance effect. For instance, unobserved motivation might affect a student's attendance and academic performance simultaneously. Hence, we employ a regression discontinuity approach to solve the potential endogeneity problem in this study. A number of studies have relied on regression discontinuity design to identify the program effects in the context of economics education (Lee and Lemieux, 2010; Dobkin et al, 2010; Chen and Okediji, 2014).

A regression discontinuity approach allows us to causally identify the lecture attendance effects using a quasi experiment design. In this quasi experiment, students who scored just below the class mean on the first exam were considered as the treatment group, and were required to attend face-to-face lectures taught by the instructor. In contrast, students in the control group, namely those who scored just above the class mean on the first exam, were not subject to the compulsory attendance policy.

To apply regression discontinuity design, only students whose first exam scores near the class mean were kept in our sample. As pointed out by Lee and Lemieux (2010), using a larger window of data could reduce variance but introduce more bias to the estimation. In this study, two samples were used in order to obtain robust estimation. Both samples consisted of certain percentage of the total number of students who scored right below the class mean and right above the class mean on their first exam in the Fall semesters of 2011 and 2012. In the first sample, we kept 20% of the total number of students. Among students in the first sample, half of them scored right below the class mean and half of them scored right above the class mean. Using the same methodology, we created the second sample and kept 40% of the total number of students. Among these students, half of them scored right above the class mean and half of them scored right below the class mean. We describe the first sample as the "20% sample" and the second sample as the "40% sample" hereafter.

Applying the regression discontinuity design described above, equation (2) is constructed.

$$y_{ij} = \eta r_{ij} + m(midterm_i - \mu) + x_{ij}\beta + \gamma_j + \varepsilon_{ij},\ \ i = 1, 2, ..., I, j = 1, 2, 3, ..., J \quad (2)$$

We estimate equation (2) using an instrumental variables (IV) method. The binary variable of whether or not a student is required to attend face-to-face lectures is used as an instrumental variable for the attendance variable, r_{ij}. If a student's first exam score is below the class mean, he or she will be required to attend the 4 face-to-face lectures before the second exam. $midterm_i$ is student i's first midterm exam score. μ is the class mean of the first midterm exam scores which is used to normalize the scores to be zero around the mean score (i.e. $midterm_i$ - μ). Following the literature in this line of research, $m(.)$ is a low order polynomial function. As described above, x_{ij} refers to various covariables affecting a student's exam performance. γ_j represents question j's specific effect, and ε_{ij} is a random disturbance term. I denotes total number of students; J denotes total number of examination questions.

5. Empirical Results

Table I reports the summary statistics of the "20% sample" and Table II reports that of the "40% sample". As shown in Tables I and II, the below mean group and the above mean group are not statistically different from each other in terms of first exam performance, prior GPA and gender. This implies that experiment and control groups are similar in many ways except for the treatment itself which is the mandatory attendance policy in this analysis. From Tables I and II, the frequency of attending face-to-face lectures for the below mean group is much higher than that for the above mean group. However, on the average, number of recorded lectures watched by the above mean group is higher than that of the below mean group. The percentage of students who never watched the 4 recorded lectures ranges from 9.09% to 36.36%.

In addition, we find that the second exam performance for the control group and the treatment group does not seem to be very different from each other. There are several plausible reasons for this. First, the treatment group performs as well as the control group on the second exam because the assignment of treatment and control group is purely random and the treatment effect is negligible. The second explanation is that mandatory attendance policy works well and helps students in the treatment group learn better so that their exam performance is similar to that of control group. The third explanation is that low-performing students have stronger motivations to work harder on second exam to be able to pass the course.

Next, to better gauge the relationship between face-to-face lecture attendance and students' examination performance, we control for other covariates to estimate the statistical model. Other control variables include whether or not a student finished watching online lectures, first exam score, gender, prior GPA, and exam question dummy variables.

Tables III, IV, V, and VI present the estimation results for two samples. As described in Equation (2), a student's second exam performance is the main dependent variable in this model. The major independent variable of interest is whether or not a student attends face-to-face lectures. There is still an endogeneity problem associated with whether or not students attend face-to-face lectures even though they are required to attend live lectures. Hence, we adopt an instrumental variable approach. In this analysis, whether or not a student is required to attend face-to-face lectures by the instructor is the instrumental variable. If a student's first exam score is below the class mean, then he or she will be required to attend face-to-face lectures.

We argue that the mandatory variable is a proper instrumental variable based on the following two reasons. First, the mandatory policy variable is highly correlated to whether or not students actually attend lectures. Second, for the group of students whose first exam score is near the class mean, being selected to control or treatment group is likely to be random. We therefore expect that the mandatory policy variable is not correlated with the random disturbance.

Tables III and IV present the first stage estimation results of the 20% and 40% samples respectively. We estimate four models and obtain similar results. Students who were required to attend lectures were more likely to attend face-to-face lectures, and the effect is statistically significant from zero. Also, the values of R-squared range from 0.34 to 0.54, and F-test statistics are large numbers and all significantly different from zero. Hence, we probably do not have the weak IV problem in this case.

The second stage estimation results are reported in Tables V and VI. For the purpose of comparison, both IV and ordinary least squares (OLS) models are presented. Estimation results of most models show that whether or not students attend face-to-face lectures has a positive impact on students' examination performance. However, the effect is not statistically significant among all models. This implies that offering face-to-face lectures in an online course does not produce beneficial effects for students. This finding is consistent with the result found in Kakish et al. (2012) but contradicts with those findings in McVey (2009) and Vernadakis et al. (2011).

One plausible explanation for the insignificant lecture attending effect is that there might be a correlation between attending face-to-face lectures and watching online course materials. For instance, when students did not attend face-to-face lectures, they could still watch online materials to prepare for examinations. Therefore, they might perform as well as students who attended the lectures. In such an instance, whether or not attending live lectures may not produce an effect on students' academic performance.

In order to test whether the face-to-face lecture attendance effect is different among students with different online viewing patterns, we divided the sample into three groups based on viewing patterns including (1) never watched, (2) watched some, and (3) finished watching online recorded lectures before the second exam. We focused on the two extreme opposite groups including students who never watched online lectures and those who finished watching online lectures, and we estimated the IV models again. Table VII shows that, for the groups of students who never watched online recorded lectures, attending face-to-face lectures yields a positive and significant effect on their examination performance in both "20% sample" and "40% sample". For example, in the 20% sample, for students who never watched online course materials, attending face-to-face lecture leads to 32.9% grade improvement.

From our analysis, a positive attendance effect is only observed for the group of students who never watched online pre-recorded lectures. One implication derived from this estimation is that offering face-to-face lecture in an online course is beneficial for low performing students who barely accessed online course materials.

Additionally, it is worth noting that if attending face-to-face lecture is a perfect substitute for accessing online course materials, a cost effective policy might be encouraging students viewing pre-recorded online materials but not requiring them to attend live lectures. To examine the association between viewing behavior and examination performance, Figures 1 and 2 are drawn. Figure 1 shows the distribution of exam 1 grades by viewing pattern using the data from the Fall of 2011. A similar pattern was found in the Fall of 2012. Students who accessed more online course materials did perform better on exam 1. Figure 2 describes the correlation between first exam and second exam scores. As shown in Figure 2, the regression discontinuity cutoff point is the mean grade of exam 1 which was 17.5 in this case. Students were divided into two groups according to number of recorded lectures watched during the period between the first and the second exam. We find that many students in the bottom half of grades distribution were those who watched less than 2 pre-recorded lectures. Hence, we conjectured that students' viewing patterns are highly correlated with their examination performance. Consequently, in terms of enhance students learning especially for low performing students, a cost effective policy might be finding ways to encourage students watching pre-recorded lectures but not necessarily requiring students to attend face-to-face lectures.

6. Conclusions

As computer technology advances, fully online programs and hybrid learning courses have become viable options. From the viewpoint of efficiency, providing supplementary options like traditional classroom instruction in online learning programs may increase students' welfare, help them learn better, and score higher on examinations. However, if providing such options does not enhance students' learning outcomes, then this provision implies higher costs and more use of resources.

To answer the question of whether or not providing face-to-face lecture options improves online learning students' grades, this study estimates the effect of attending face-to-face lectures on students' examination performance in an online learning Intermediate Microeconomics course. By using a regression discontinuity approach, we attempted to causally identify the face-to-face lecture attendance effect in a traditional fully online course.

Our estimation results demonstrate that, on the average, attending face-to-face lectures does not improve online learning students' examination performance. However, for the group of students who did not or chose not to access online course materials, attending face-to-face lectures did produce a significant and positive effect on their grades.

As revealed from this study, on the average, offering face-to-face lecture options to online leaning students requires more resources but does not significantly improve students' examination performance. In order to enhance students learning particular for low performing students, a cost effective policy option might not be requiring students to attend face-to-face lectures but discovering ways to encourage or require students accessing pre-recorded lectures.

When evaluating the effectiveness of hybrid teaching style in online learning programs, this study provides useful information to policymakers and educators in higher education. More research is needed in the future to thoroughly assess the learning outcomes under online learning and hybrid learning instruction.

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Table I: Summary Statistics (20% Sample)

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
	Fall 2011				
	Students whose exam 1 scores are right above the class mean				
Semester Grade (out of 100)	11	69.468	8.0406	54.800	80.300
Attendance*		1.1818	1.4013	0.0000	4.0000
Exam 1 Score (out of 25)		18.409	0.584	18.000	19.500
Exam 2 Score (out of 25)		18.682	3.227	13.000	23.000
Prior GPA (out of 100)		80.936	3.1280	75.000	86.000
Number of Recorded Lectures Watched		3.2727	1.2517	0.0000	4.0000
Never Watched Recorded Lectures		0.3636	0.5045	0.0000	1.0000
	Fall 2011				
	Students whose exam 1 scores are right below the class mean				
Semester Grade (out of 100)	11	66.477	8.749	48.200	81.200
Attendance*		3.0909	1.3751	0.0000	4.0000
Exam 1 Score (out of 25)		16.364	0.452	16.000	17.000
Exam 2 Score (out of 25)		18.773	3.011	12.000	23.000
Prior GPA (out of 100)		78.591	7.242	67.000	89.000
Number of Recorded Lectures Watched		2.6364	0.6742	0.0000	4.0000
Never Watched Recorded Lectures		0.3636	0.5045	0.0000	1.0000
	Fall 2012				
	Students whose exam 1 scores are right above the class mean				
Semester Grade (out of 100)	11	75.164	6.656	63.500	85.200
Attendance*		0.6364	0.6742	0.0000	2.0000
Exam 1 Score (out of 25)		19.045	0.472	18.500	19.500
Exam 2 Score (out of 25)		17.864	3.715	12.500	22.500
Prior GPA (out of 100)		79.050	5.776	70.000	87.000
Number of Recorded Lectures Watched		3.3636	1.0593	0.0000	4.0000
Never Watched Recorded Lectures		0.1818	0.4045	0.0000	1.0000
	Fall 2012				
	Students whose exam 1 scores are right below the class mean				
Semester Grade (out of 100)	11	69.518	5.007	59.800	78.000
Attendance*		3.6364	0.9244	1.0000	4.0000
Exam 1 Score (out of 25)		17.636	0.323	17.000	18.000
Exam 2 Score (out of 25)		18.091	3.121	10.500	22.500
Prior GPA (out of 100)		77.091	7.0492	65.000	87.000
Number of Recorded Lectures Watched		2.6364	1.2863	0.0000	4.0000
Never Watched Recorded Lectures		0.3636	0.5045	0.0000	1.0000

Note: The *Attendance* variable refers to number of times a student attended face-to-face lectures. There were 4 face-to-face lectures offered by the instructor after exam 1 and before exam 2.

Table II: Summary Statistics (40% Sample)

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
	Fall 2011				
	Students whose exam 1 scores are right above the class mean				
Semester Grade (out of 100)	22	70.909	7.385	54.800	81.000
Attendance*		0.6818	1.1291	0.0000	4.0000
Exam 1 Score (out of 25)		19.386	1.133	18.000	21.000
Exam 2 Score (out of 25)		18.909	3.165	11.000	23.000
Prior GPA (out of 100)		80.227	5.1642	70.000	88.700
Number of Recorded Lectures Watched		3.3182	1.0861	0.0000	4.0000
Never Watched Recorded Lectures		0.1818	0.3948	0.0000	1.0000
	Fall 2011				
	Students whose exam 1 scores are right below the class mean				
Semester Grade (out of 100)	22	65.445	9.086	48.200	81.200
Attendance*		3.3636	1.0486	0.0000	4.0000
Exam 1 Score (out of 25)		15.364	1.274	13.000	17.000
Exam 2 Score (out of 25)		17.841	3.427	10.000	23.000
Prior GPA (out of 100)		78.386	5.3228	67.000	89.000
Number of Recorded Lectures Watched		2.6364	1.0022	0.0000	4.0000
Never Watched Recorded Lectures		0.3636	0.4924	0.0000	1.0000
	Fall 2012				
	Students whose exam 1 scores are right above the class mean				
Semester Grade (out of 100)	22	77.041	7.4353	63.500	92.300
Attendance*		0.5455	0.9625	0.0000	4.0000
Exam 1 Score (out of 25)		19.523	0.645	18.500	20.500
Exam 2 Score (out of 25)		18.364	3.646	12.500	23.500
Prior GPA (out of 100)		74.325	16.879	7.000	87.000
Number of Recorded Lectures Watched		3.5000	0.9129	0.0000	4.0000
Never Watched Recorded Lectures		0.0952	0.2942	0.0000	1.0000
	Fall 2012				
	Students whose exam 1 scores are right below the class mean				
Semester Grade (out of 100)	22	68.255	5.4120	54.400	78.000
Attendance*		3.6364	0.7895	1.0000	4.0000
Exam 1 Score (out of 25)		16.750	1.131	14.500	18.000
Exam 2 Score (out of 25)		17.159	3.137	10.500	22.500
Prior GPA (out of 100)		77.636	5.1413	65.000	87.000
Number of Recorded Lectures Watched		2.4091	1.4690	0.0000	4.0000
Never Watched Recorded Lectures		0.3636	0.4924	0.0000	1.0000

Note: The *Attendance* variable refers to number of times a student attended face-to-face lectures. There were 4 face-to-face lectures offered by the instructor after exam 1 and before exam 2.

Table III: Determinants of Lecture Attendance

(First Stage Estimation, 20% Sample)

Independent Variable	Model (I)	Model (II)	Model (III)	Model (IV)
Students were required to attend lectures	0.760**	0.760**	0.725**	0.715**
	(0.159)	(0.160)	(0.142)	(0.137)
Students finished watching online course material		-0.00242	0.0293	-0.0261
		(0.0654)	(0.0725)	(0.0776)
Students' exam 1 score (dmean)		0.137	0.105	0.101
		(0.114)	(0.0967)	(0.0935)
Students' exam 1 score (dmean) Squared		-0.0404	-0.0497	-0.0393
		(0.0728)	(0.0684)	(0.0702)
Prior GPA			0.00500	0.00469
			(0.00694)	(0.00727)
Male			-0.164**	-0.165**
			(0.0735)	(0.0748)
Exam question dummies	NO	NO	NO	YES
Constant	0.178	0.178	-0.107	-0.0429
	(0.138)	(0.144)	(0.565)	(0.598)
R-squared	0.346	0.346	0.383	0.426
F-test	126.03**	94.39**	73.63**	12.64**
Sample Size	718	718	718	718

Note: The dependent variable is whether or not a student attended the specific face-to-face lecture. Robust standard errors are reported and are adjusted for student clustering. "**" is significant at 0.05 Type I error level.

Table IV: Determinants of Lecture Attendance

(First Stage Estimation, 40% Sample)

Independent Variable	Model (I)	Model (II)	Model (III)	Model (IV)
Students were required to attend lectures	0.568***	0.568***	0.560***	0.560***
	(0.0858)	(0.0868)	(0.0833)	(0.0849)
Students finished watching online course material		0.00144	0.00236	-0.0257
		(0.0368)	(0.0377)	(0.0383)
Students' exam 1 score (dmean)		-0.0376**	-0.0402**	-0.0379**
		(0.0166)	(0.0165)	(0.0172)
Students' exam 1 score (dmean) Squared		-0.00623*	-0.00737**	-0.00599
		(0.00373)	(0.00362)	(0.00484)
Prior GPA			0.00392**	0.00414**
			(0.00173)	(0.00176)
Male			-0.0756	-0.0766
			(0.0514)	(0.0519)
Exam question dummies	NO	NO	NO	YES
Constant	0.276***	0.276***	0.0159	0.0226
	(0.0597)	(0.0671)	(0.128)	(0.153)
R-squared	0.511	0.511	0.522	0.543
F-test	510.2**	382.39**	266.57**	42.70**
Sample Size	1,471	1,471	1,471	1,471

Note: The dependent variable is whether or not a student attended the specific face-to-face lecture. Robust standard errors are reported and are adjusted for student clustering. "**" is significant at 0.05 Type I error level.

Table V: Face-to-Face Lecture Attendance and Student Exam Performance (20% Sample)

	IV				OLS			
Independent Variable	Model (I)	Model (II)	Model (III)	Model (IV)	Model (V)	Model (VI)	Model (VII)	Model (VIII)
Students attended face-to-face lecture	0.0863	0.0865	0.0806	0.0791	0.0331	0.0344	0.0355	0.0175
	(0.101)	(0.101)	(0.107)	(0.106)	(0.0369)	(0.0375)	(0.0361)	(0.0549)
Students finished watching online course material		0.00748	0.0126	0.0106		0.00883	0.0128	0.00869
		(0.0380)	(0.0396)	(0.0408)		(0.0334)	(0.0343)	(0.0425)
Students' exam 1 scores (dmean)		0.0258	0.0193	0.0185				0.00287
		(0.0292)	(0.0350)	(0.0352)				(0.0408)
Students' exam 1 scores (dmean) Squared		-0.0109	-0.00938	-0.00853				-0.00803
		(0.0171)	(0.0183)	(0.0192)				(0.0209)
Prior GPA			0.00288	0.00291			0.00338	0.00340
			(0.00367)	(0.00365)			(0.00321)	(0.00349)
Male			0.0187	0.0182			0.0139	0.00707
			(0.0436)	(0.0424)			(0.0382)	(0.0391)

Exam question dummies	NO	NO	NO	YES	NO	NO	NO	YES
Constant	0.731**	0.729**	0.494	0.430	0.757**	0.753**	0.477	0.437
	(0.0796)	(0.0818)	(0.296)	(0.295)	(0.0303)	(0.0349)	(0.275)	(0.292)
R-squared	.	.	.	.	0.002	0.002	0.004	0.189
Sample Size	718	718	718	718	718	718	718	718

Note: The dependent variable is the percentage of scores awarded for the question. Robust standard errors are reported and are adjusted for student clustering"**" is significant at 0.05 Type I error level. "**" is significant at 0.05 Type I error level.

Table VI: Face-to-Face Lecture Attendance and Student Exam Performance (40% Sample)

	IV				OLS			
Independent Variable	Model (I)	Model (II)	Model (III)	Model (IV)	Model (V)	Model (VI)	Model (VII)	Model (VIII)
Students attended face-to-face lecture	0.0417	0.0406	0.0442	0.0521	-0.00247	-0.000616	3.51e-05	0.0353
	(0.0981)	(0.0992)	(0.0999)	(0.100)	(0.0271)	(0.0285)	(0.0274)	(0.0360)
Students finished watching online course material		-0.00288	0.000638	-0.00941		0.00854	0.0127	-0.0104
		(0.0296)	(0.0290)	(0.0305)		(0.0265)	(0.0257)	(0.0299)
Students' exam 1 scores (dmean)		0.0203	0.0214	0.0237				0.0212**
		(0.0175)	(0.0173)	(0.0172)				(0.0106)
Students' exam 1 scores (dmean) Squared		-0.00387	-0.00353	-0.00215				-0.00238
		(0.00388)	(0.00367)	(0.00371)				(0.00345)
Prior GPA			0.000665	0.000922			0.000741	0.000994
			(0.00118)	(0.00123)			(0.00107)	(0.00107)
Male			0.0414	0.0420			0.0375	0.0405
			(0.0294)	(0.0293)			(0.0285)	(0.0273)

Exam question dummies	NO	NO	NO	YES	NO	NO	NO	YES
Constant	0.760**	0.762**	0.685**	0.610**	0.770**	0.766**	0.688**	0.616**
	(0.0688)	(0.0718)	(0.0831)	(0.0978)	(0.0210)	(0.0256)	(0.0908)	(0.0979)
R-squared	.	.	.	.	0.001	0.001	0.002	0.203
Sample Size	1,471	1,471	1,471	1,471	1,471	1,471	1,471	1,471

Note: The dependent variable is the percentage of scores awarded for the question. Robust standard errors are reported and are adjusted for student clustering"**" is significant at 0.05 Type I error level. "**" is significant at 0.05 Type I error level.

Table VII: Face-to-Face Lecture Attendance and Student Exam Performance
(By Viewing Online Lecture Patterns)

	Watch Online Lecture Pattern	Sample Size	IV
20% Sample	Finished Watching Online Lectures	305	0.209 (0.217)
	Never Watched Online Lectures	205	0.3290** (0.123)
40% Sample	Finished Watching Online Lectures	319	0.0703 (0.0947)
	Never Watched Online Lectures	402	0.3560** (0.137)

Note: The dependent variable is percentage of scores awarded for the question. Covariates include whether or not students attended face-to-face lecture, students' exam 1 scores (dmean), Students' exam 1 scores (dmean) Squared, prior GPA, gender, and exam question dummies. Robust standard errors are reported and are adjusted for student clustering. "**" is significant at 0.05 Type I error level. "**" is significant at 0.05 Type I error level.

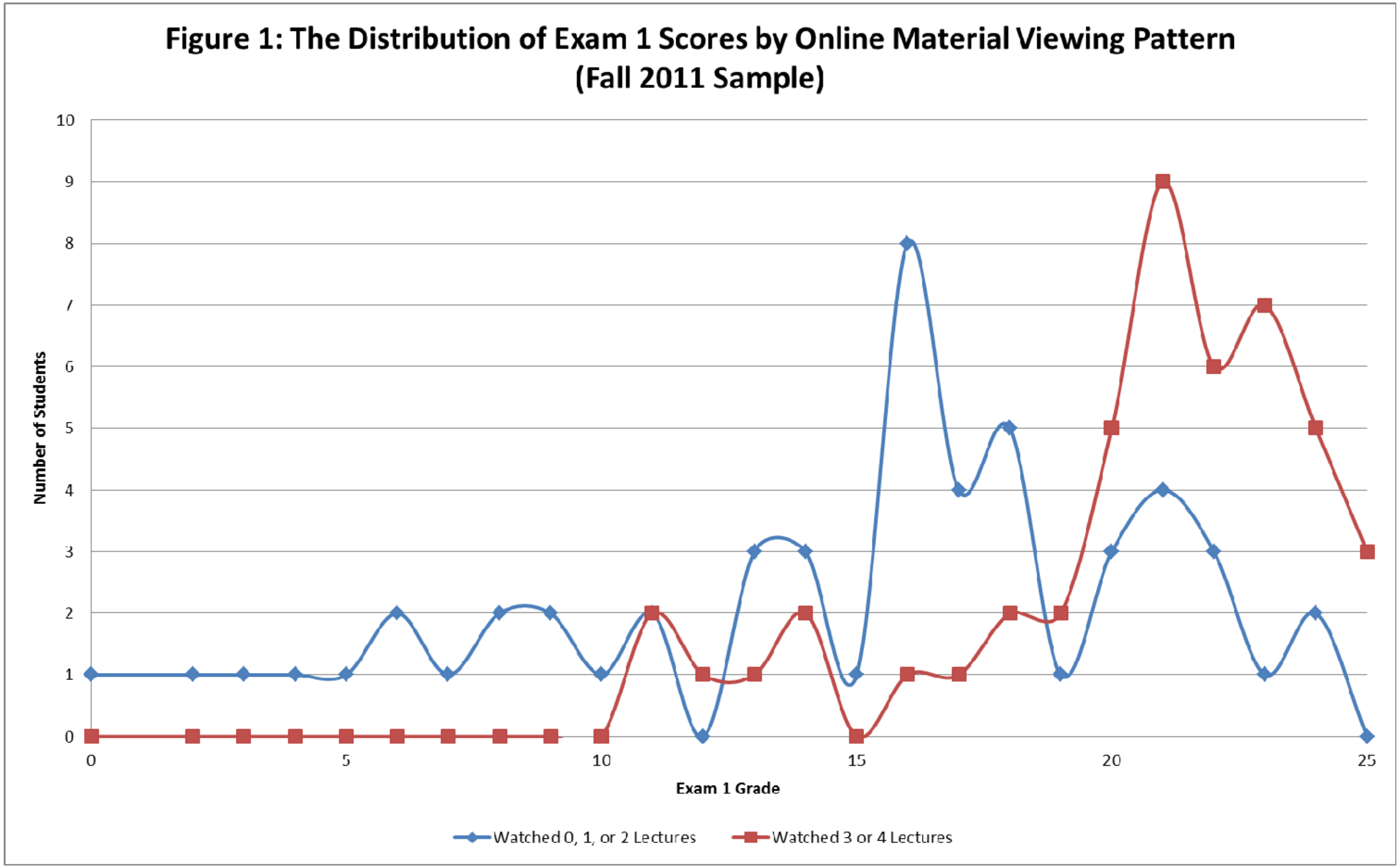
Figure 1: The Distribution of Exam 1 Scores by Online Material Viewing Pattern
(Fall 2011 Sample)
Number of Students
Exam 1 Grade
0
1
2
3
4
5
6
7
8
9
10
0
5
10
15
20
25
Watched 0, 1, or 2 Lectures
Watched 3 or 4 Lectures

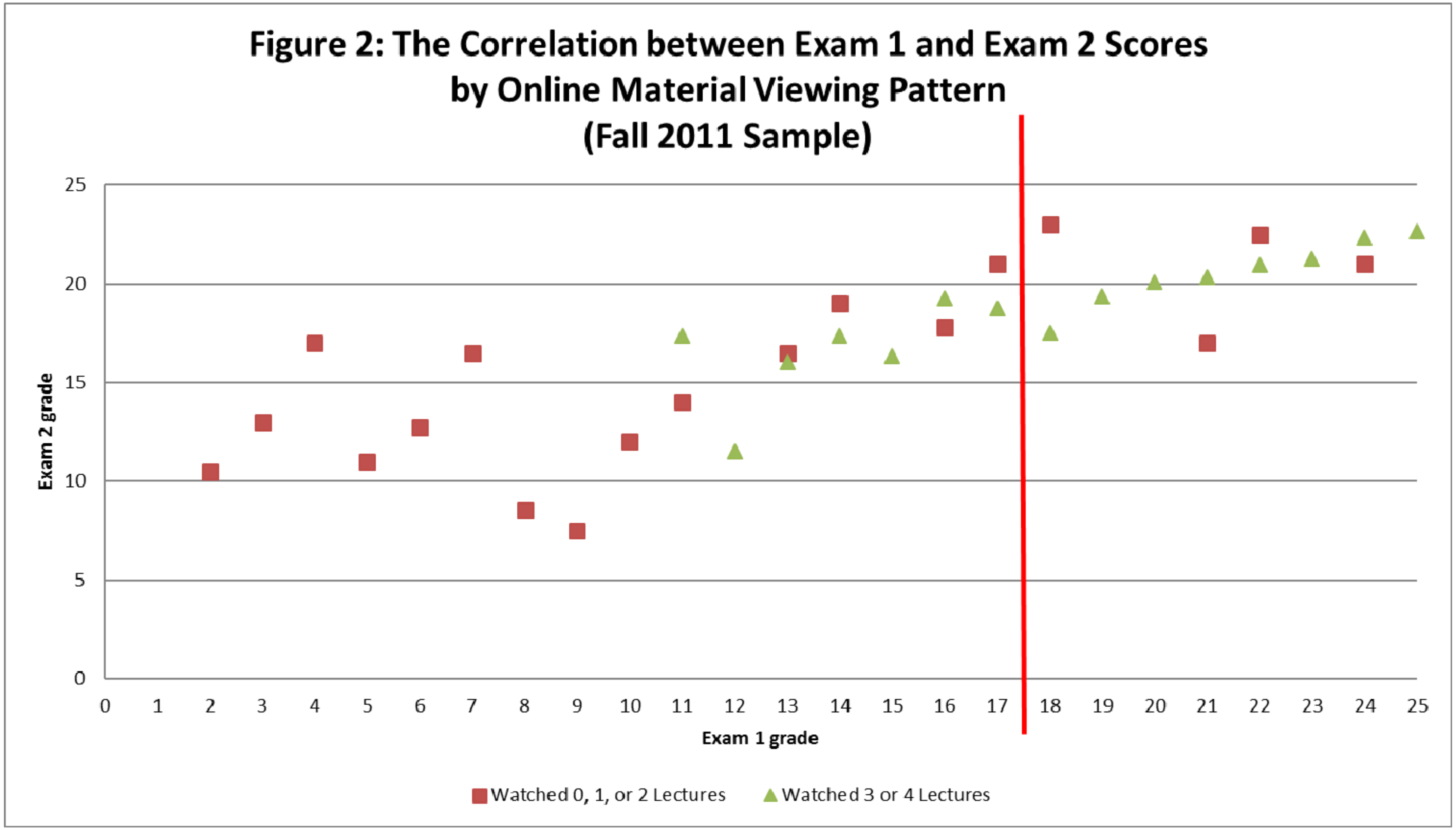
Figure 2: The Correlation between Exam 1 and Exam 2 Scores by Online Material Viewing Pattern (Fall 2011 Sample)
Exam 2 grade
0
5
10
15
20
25
Exam 1 grade
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Watched 0, 1, or 2 Lectures
Watched 3 or 4 Lectures