The Impact of Online Lectures on Student Learning

October 2020

Abstract

Digitization of higher education is fundamentally changing students' academic experience and their learning process. Traditional live lectures are increasingly being replaced with online lectures. We conduct a field experiment at a major research university where students are randomly assigned to live lectures versus watching these exact same lectures online. We estimate whether assignment to online lecture affects students' exam performance and academic experience. This document provides the pre-analysis plan.

1. Background

In the exceptional circumstances prompted by COVID-19, universities around the world have massively increased the number of courses taught online. Even before 2020, the digitization of higher education began to transform the academic experience and learning process for university students. However, very limited research exists on how students are impacted by the shift to online lectures.

In this paper, we investigate how the introduction of online lectures affects student performance and university experience. We study a European research university that was forced to introduce online lectures as part of social distancing measures in 2020. In this setting, we assign students to a rotating attendance schedule that determines whether students attend live lectures or watch the same lectures online. Assignment to live or online lectures is determined by a random number – the last digit of the student identification number.

We aim to answer the following research questions:

1. Do students perform better on exam questions when the content of the question was covered in an online lecture compared to a traditional in-person lecture? (Exam performance)
2. Do online lectures affect subsequent attendance, course dropout, course passing, and student grades? (Academic trajectory)
3. Do online lectures affect students' social interactions, satisfaction with different course features, study habits, and overall learning experience? (Subjective outcomes)
4. Does assignment to online attendance affect study dropout, completion of the first year, elective course choices, and major switching? (Longer run outcomes)

2. Experimental design

Our field experiment takes place at a European research university. All first-year bachelor and master students are randomly assigned into five attendance groups. The assignment is based on a random number – the last digit of the student ID number. Based on a rotating block schedule, each attendance group is permitted to attend some lectures in person, and others online via Zoom. More specifically, each attendance group is allowed to come to the university two days per week[1]. The randomization into attendance groups implies that, for any given lecture, some students receive the content in person and others receive it via an online lecture. Our within-subject design means that a given student attends some lectures online and others in person. Therefore, our experimental design creates exogenous variation in whether a given lecture was attended online and in the share of lectures a student attended online.

By linking lecture content to exam questions, our design allows us to compare student performance based on whether they attended a lecture online or in person. In other words, we will evaluate the impact of online lecture assignment on student performance through exam questions covering material taught in the corresponding lecture.

2.1 Randomization Method

All first-year students are randomly assigned into five attendance groups based on the last digit of their student ID number. Each week, each group can come to university for two full days, according to a rotating block schedule. This randomization implies that for any given lecture, some students receive the content in person and others receive it via an online lecture.

2.2 Compliance with the Assigned Treatment

Students assigned to the live in-person lecture treatment always have the option to stay home and watch the lecture online. We expect that a substantial number of students assigned to the live lecture will opt to watch lectures online. This means that the treatment effect of watching a class online is an intention-to-treat (ITT) effect and it will likely be underestimated since some students who were meant to be in the live class will choose to watch a lecture online. In addition, students assigned to watch online may choose not to attend at all. Using Zoom attendance data, we will compute the proportion of students that comply with the live assignment and provide bounds of the true treatment effect of attending a class live. Importantly, the ITT estimate represents the policy-relevant parameter, as educators and university decision makers cannot force students to attend live.

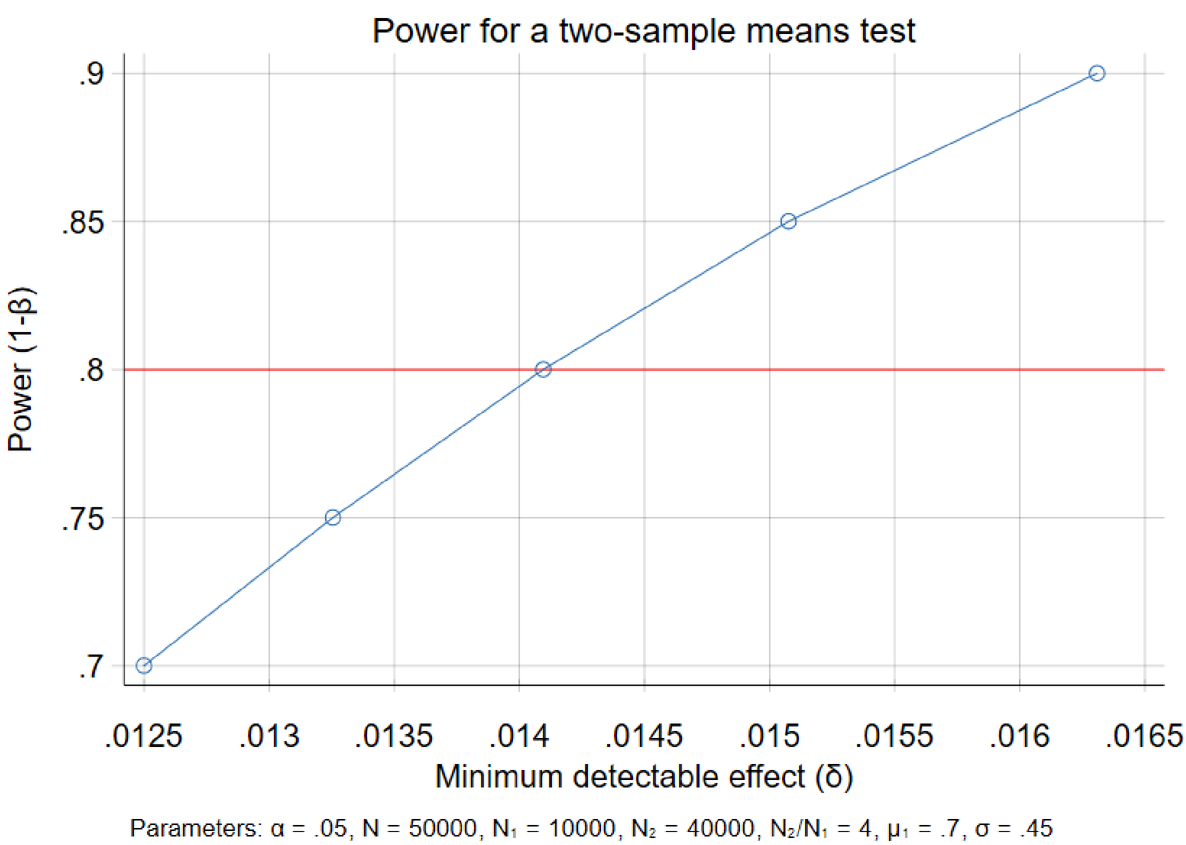
[1] At the start of the term, each attendance group could only attend for two 4-hour blocks per week. Early in the term, the schedule changed to allow students to attend for two full days per week.

2.3 Statistical Power

We expect to observe at least 1,000 students. For each of these students we expect to observe at least 50 responses to different multiple choice exam questions resulting in an overall sample of about 50,000 observations.

Figure 1 shows the results of a simple power calculation and suggests that we have sufficient statistical power to detect fairly small effect sizes. We assume a sample size of 50,000 exam questions, power of .8, and treatment arm that is 80% of the entire sample. For the binary outcome, we assume a mean of 0.7 correct answers and a standard deviation of 0.45. We conduct a two-sample means test to calculate the minimum detectable effects (MDEs) of a treatment effect significant at the five percent level. Figure 1 below shows the MDEs for different levels of power. Here, δ refers to the difference between the in-person group mean and the online group mean for a given exam question. With a power of .8 we can detect differences between the treatment and control group that are larger than 0.0141. This corresponds to a minimum detectable treatment effect of 0.031 standard deviations.

Figure 1: Power Analysis



3. Empirical Analysis

Our experimental design creates exogenous variation in whether a given lecture was attended online and in the share of lectures a student attended online. All our estimates will be intention-to-treat (ITT) effects.

3.1 Primary Outcomes

The primary outcome of our exam question analysis is whether a student answered a given multiple choice question correctly. We link each exam question to lecture content to determine whether a given student-course-question observation is treated. This will allow us to directly estimate the impact of online lecture assignment on the probability of successfully answering a specific exam question.

The primary outcomes for our student-course level analysis are subsequent lecture attendance, course dropout, course passing, and student grades. These outcomes capture students' academic trajectory. Course dropout and passing are binary outcomes, indicating if a student remained in the course or passed the course. The overall course grade is a continuous measure.

All primary outcomes will be measured through administrative data.

3.2 Secondary Outcomes

Secondary outcomes are student subjective outcomes as well as longer run educational outcomes. Student subjective outcomes are reported social interactions, satisfaction with different course features, study habits, and their overall learning experience. These outcomes will be measured through an endline survey.

Longer run educational outcomes will be study dropout, completion of the first year, elective course choices, and major switching. These outcomes will be measured through administrative data – if we receive the necessary data access.

3.3 Estimation

Our goal is to estimate the effect of being assigned to an online-lecture on student outcomes. : We will analyze our data at two levels. First, in the exam question analysis, we use a dataset where each student-exam-question-answer is one observation. Second, in our student-course level analysis, we use a dataset where each student-course combination is one observation.

Equation (1) shows our empirical model for the exam question analysis:

$$Y_{iq} = \alpha_1 Online\ Lecture_{iq} + X_i'\gamma + \theta + \varepsilon_{iq} \qquad (1)$$

where Y_{iq} is a binary indicator taking the value of 1 if student i correctly answers exam question q and 0 otherwise. $Online\ Lecture_{iq}$ is an indicator denoting if student i was assigned to an online lecture where the content of question q was taught. α_1 is the parameter of interest and will capture the causal effect of attending a lecture online rather than in person. We augment equation (1) with the vector X_i containing baseline control variables. The baseline variables include student demographics such as gender, age, and nationality. We always include course fixed effects θ.

Equation (2) shows our empirical model for the student-course analysis:

$$Y_{ic} = \beta_1 Share\ Online\ Lectures_{ic} + X_i'\gamma + \theta + \varepsilon_{ic} \qquad (2)$$

where Y_{ic} is the course specific outcome of student i in course c. Primary outcomes are subsequent attendance, course dropout, course passing, and the overall course grade. Secondary outcomes are measures of students' subjective learning experience, satisfaction, study habits, and social interactions. $Share\ Online\ Lectures_{ic}$ is a continuous measure of the share of assigned online lectures of student i in course c. The treatment effect of interest is β_1, capturing the effect of the share of assigned online lectures. To study dynamic effects, we will also estimate a variation of model (2) that tests whether attending a live class early in the semester has unique effects on academic and subjective outcomes.

We will estimate Equations (1) and (2) with OLS and cluster standard errors at the student and course level. We will additionally provide p-values based on randomization inference with 10,000 repetitions following Young (2018).

3.4 Subgroup Analysis

We will estimate treatment effects for different subsamples of students. Specifically we will test treatment heterogeneity by:

- Sex
- Past achievement (median sample split)
- Nationality: Native vs. foreign students / High school language of instruction
- Study habits: High vs. low self-study intensity (median sample split)
- Study habits: Individual vs. group learners
- Conscientiousness (median sample split)
- Extraversion (median sample split)
- Travel time to university – as a proxy for the lecture attendance cost
- Study major

References

Young, A. (2018), "Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results," Quarterly Journal of Economics, 134(2), 557–598.