

# Distance Learning in Higher Education: Evidence from a Randomised Experiment

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- Edutech sector is booming but we still know relatively little about the causal effects of many technological tools applied in education (*Escueta et al., 2017*)
- One primary area of interest is online learning tools in higher education
  - potential to reduce costs and extend access.
- Credible empirical evidence is extremely scant.



- Very many studies across many disciplines but few with credible identification (small samples, one or few subjects, mixed results) (US Department of Education, 2010).
  - RCT papers: Alpert et al., AER(P&P) 2016; Bowen et al., JPAM 2014; Figlio et al., JOLE 2013.
  - IV papers: *Bettinger et al., AER 2017; Coates et al., EER 2004; Xu et al., 2013.*
- Our contribution:
  - RCT, large sample, standard institution, clear counterfactuals;
  - analysis of student choices and mechanism.

## What we do and what we find

- We study a randomised experiment at the University of Geneva where students were given random access to live streaming of lectures
- We find that
  - students take up only rarely, apparently when the cost of class attendance is particularly high
  - exam performance goes up for high ability students and down for low ability ones
  - small effects on attendance.
- We rationalise the findings with a simple model of attendance choices
  - the counterfactual for the good students is no attendance and for the bad students it is class attendance.

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## The experimental context

- First year bachelor students in "economics&management" and "international relations"
- Two semesters
  - Spring 2017 (Feb-May); Fall 2017 (Sep-Dec)
- 8 compulsory courses with lectures taking place in one auditorium (450 seats)
  - Spring 2017: introductory macro, probability&statistics, human resource management
  - Fall 2017: introductory micro (3 parallel sections, 2 in French 1 in English), mathematics, introduction to management
- Students in the experiment also take other courses that are never streamed

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## Courses, language and enrolment

Term	Course	Language	Size	Bachelor
1g	Introductory macroeconomics	French	386	EM
inq	Probability	French	490	EM&IR
S	Human Resource Management	French	242	EM
	Introduction to microeconomics	French	460	EM
_	Introduction to microeconomics	French	357	IR
Fall	Introduction to microeconomics	English	241	EM&IR
	Mathematics	French	481	EM&IR
	Introduction to management	French	261	EM

- Live streaming of the lectures (not the TA sessions)
  - access via usual university credentials (same as for email, exam enrolment, et.)
  - access opens 10 minutes before the lecture starts and closes 10 minutes after the end
  - access possible from any internet-connected device
  - video shows lecturer and slides
  - video can be zoomed and frozen
  - no recording of the streamed videos for later access
- No enforcement of physical class attendance or non-attendance
  - students can always go to the classroom

## Live streaming example



- Access to the streaming platform is randomised across students and weeks of the term
  - access given for all the courses the students are enrolled for.
- Enrolment and assignment to treatment
  - 13-week term (+1 week mid-term break)
  - week 1 the system is presented to the students
  - they have two weeks to enrol in the online learning platform (used for streaming but also for sharing documents, announcements, submitting assignments, et.)
  - towards the end of week 2 they receive notification about treatment assignment

# Notification email

Dear students,

In the context of the streaming project, you will have access to live streaming for all the courses you are attending, in the following weeks of the spring term :

Term week	Week of year	Streamed course available to you :
3	10	no
4	11	no
5	12	yes
6	13	yes
7	14	yes
8	15	no
9	16	Easter Holiday
10	17	yes
11	18	yes
12	19	yes
13	20	no
14	21	yes

To watch the live videos of the classes, you need to connect to the following web page :

https://cms.unige.ch/gsem/streaming

using your ISIs credentials (your usual login and password for UniGe services). Your access will be active 10 minutes before the beginning of the class. The first time you connect to this service, you might be asked to choose a teaching entity; select "Université de Genève" (as shown in the image):

# The randomisation (2)

- Three randomisation groups:
  - 1 <u>never-access</u> (15%) are never given access
  - 2 sometimes-access (70%) are given access to streaming in some random weeks
  - 3 always-access (15%) are given access in all weeks
- Assignment for the sometimes-access group
  - in Spring 2017, every week 50% of the students in the sometime-access group are assigned to treatment
  - in Fall 2017, we vary the % of students assigned to treatment across weeks, ranging between 20% and 80%

weeks											
3	4	5	6	7	8	9	10	11	12	13	14
80%	40%	60%	20%	80%	40%	break	60%	20%	80%	40%	60%

Data

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- We combine several sources of information:
  - 1 enrolment lists with random assignment to treatment
  - 2 administrative records of the students
  - 3 log files from the streaming server
  - 4 question-by-question exam results (only final)
  - 5 proxies of attendance in each course-week session (only for Fall 2017)
- Particularly important is the **mapping of exam questions to weeks**, which allows us to have outcomes at the student-course-week level
- Attendance is estimated based on classroom pictures ( $\sim 2$  per session) and subjective evaluations from over 100 *MTurk* evaluators per session

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## The data: student sample

	Spring 2017	Fall 2017	Total
	(21	1,000	12(01
N. of students	621	1,000	1 621
N. of courses per student	1.8	1.8	1.8
Max n. courses per student	3	3	6
N. of students in both waves		162	
N. of courses per student in both waves	4.01		
Min courses per student in both waves		2	
Max courses per student in both waves		6	

### Descriptive statistics on students

	Never-	access	Sometim	es-access	Always-access	
	Mean	SD	Mean	SD	Mean	SD
Weeks with access	0.000	0.000	5.693	1.631	11.000	0.000
Swiss=1	0.612	0.488	0.602	0.490	0.584	0.494
Female=1	0.570	0.496	0.492	0.500	0.513	0.501
High-school grade <sup>a</sup>	0.338	0.191	0.330	0.182	0.339	0.186
Mother with college	0.367	0.483	0.355	0.479	0.328	0.470
Father with college	0.422	0.495	0.424	0.494	0.450	0.498
Drop-out <sup>b</sup>	0.286	0.453	0.295	0.456	0.308	0.463
Grade <sup>c</sup>	0.047	0.870	-0.026	0.958	0.049	0.923

<sup>*a*</sup> Share above the passing grade.

<sup>b</sup> Share of students not taking at least one exam.

<sup>c</sup> Average normalised grade over all courses.

## Ability distributions



## Weekly random assignment



## Random assignment, use and take-up

Data

Week		Spring 2017	7	Fall 2017			
	Access	Streamed	Take-up	Access	Streamed	Take-up	
3	0.497	0.059	0.119	0.679	0.052	0.077	
4	0.525	0.057	0.108	0.425	0.049	0.115	
5	0.484	0.040	0.083	0.556	0.066	0.119	
6	0.549	0.058	0.106	0.284	0.026	0.092	
7	0.503	0.042	0.083	0.700	0.082	0.118	
9	0.471	0.031	0.067	0.416	0.040	0.096	
10	0.536	0.058	0.107	0.571	0.064	0.111	
11	0.501	0.049	0.097	0.306	0.035	0.115	
12	0.482	0.049	0.101	0.692	0.077	0.112	
13	0.499	0.039	0.079	0.424	0.055	0.130	
14	0.525	0.037	0.070	0.585	0.074	0.126	
Total	0.507	0.047	0.093	0.513	0.056	0.110	

## Estimated class attendance

	Enrollment	Mturk evaluations		
		mean	median	std.dev.
Micro (FR1)	369	226.08	173.89	170.80
Micro (FR2)	513	224.26	186.33	128.04
Micro (EN)	249	134.80	99.14	129.32
Math	486	201.66	165.40	118.57
Management	287	214.40	172.57	128.67

## **Classroom pictures**



## **Classroom pictures**



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## Distribution of total take-up



# Distribution of total take-up by ability

Data



## Weekly take-up by ability



## Take-up and shocks

	D	aily weath	Influenza outbreak		
Ability	Bad	Normal	Good	No	Yes
Bottom 20%	0.142	0.091	0.117	0.090	0.130
	(0.030)	(0.012)	(0.026)	(0.012)	(0.024)
Mid 60%	0.213	0.109	0.170	0.113	0.156
	(0.021)	(0.008)	(0.018)	(0.008)	(0.017)
Top 20%	0.161	0.084	0.106	0.089	0.087
	(0.037)	(0.012)	(0.023)	(0.013)	(0.019)
All	0.189	0.101	0.147	0.104	0.138
	(0.016)	(0.006)	(0.013)	(0.006)	(0.012)

Predicted probabilities of take-up. Standard errors in parenthesis.



### The experimental effects on exam performance

• For each student-course-week, we regress performance on the exam questions related to that course-week on treatment status:

$$y_{icw} = \alpha_0^1 + \alpha_1^1 [assigned]_{icw} + \delta_c^1 + \theta_w^1 + \eta_i^1 + \epsilon_{cw}^1$$
  
$$y_{icw} = \alpha_0^2 + \alpha_1^2 [streamed]_{icw} + \delta_c^2 + \theta_w^2 + \eta_i^2 + \epsilon_{cw}^2$$

- $y_{icw} = 1$  if *i* answered correctly to the question(s) in exam *c* referring to material covered in week *w*
- Second equation estimated using [assigned]<sub>icw</sub> as instrument
  - first-stage coefficient is 0.123(0.003)

## The experimental effects on exam performance

Data

	Ra	Random effects			Fixed effects			
	ITT	ATT	OLS	ITT	ATT	OLS		
all students	0.001	0.006	-0.006	0.003	0.023	-0.005		
	(0.005)	(0.042)	(0.011)	(0.005)	(0.043)	(0.010)		
By ability gro	oup <sup>d</sup>			I				
Low	-0.019**	-0.179*	-0.020	-0.019**	-0.178*	-0.024		
	(0.009)	(0.098)	(0.027)	(0.009)	(0.102)	(0.027)		
Mid	-0.000	-0.002	-0.003	0.000	0.001	-0.005		
	(0.006)	(0.047)	(0.013)	(0.006)	(0.050)	(0.013)		
High	0.025**	0.245**	-0.011	0.023**	0.241**	-0.011		
	(0.010)	(0.111)	(0.026)	(0.011)	(0.121)	(0.028)		
Obs. <sup>e</sup>	23766	23766	23766	23766	23766	23766		
Mean and St	d.dev. (in pa	arentheses)	of the depe	endent varial	ole:			
all students	0.545	0.545	0.545	0.545	0.545	0.545		
	(0.378)	(0.378)	(0.378)	(0.378)	(0.378)	(0.378)		
By ability group <sup>d</sup>								
It. Hildebrand, Lucch	etti& Pellizzari	Dis	stance Learning	0.505	0 505	USI		

# ITT by ability deciles



ive statistics

## Figure 1 from Bettinger et al., AER 2017



FIGURE 1. EFFECT OF TAKING A COURSE ONLINE, INSTEAD OF IN-PERSON, FOR EACH DECILE OF PRIOR GPA

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The experimental effects on attendance

• Few observations (42) but still interesting to look at this week-class level regression:

$$attendance_{cw} = a_0^1 + a_1^1 [\# assigned]_{cw} + b_c^1 + e_{cw}^1$$
  
$$attendance_{cw} = a_0^2 + a_1^2 [\# streamed]_{cw} + b_c^2 + e_{cw}^2$$

- Observations are weighted by the inverse of the std.dev. of the Mturk evaluations
- Second equation estimated using  $[\# assigned]_{cw}$  as instrument
  - first-stage coefficient is 0.121(0.013)

### The experimental effects on class attendance

OLS	OLS	IV						
-0.079**	-	-						
(0.037)								
-	-0.431	-0.654**						
	(0.260)	(0.290)						
42	42	42						
Descriptive stat. of the dep. variable:								
153.6	153.6	153.6						
37.1	37.1	37.1						
	OLS -0.079** (0.037) - 42 tat. of the du 153.6 37.1	OLS         OLS           -0.079**         -           (0.037)         -           -0.431         (0.260)           42         42           stat. of the dep. variab         153.6           153.6         153.6           37.1         37.1						

The dependent variable is the median evaluation of the classroom pictures by the MTurk evaluators. All observations are weighted by the inverse of the standard deviation of the individual evaluations.

### The experimental effects on attendance

- For each student assigned to treatment there are -.08 students in class
  - offer streaming to all students in a class of 100, 8 fewer students in class
- Students stream more when there are more people in the classroom
- For each student streaming there are approx. -0.7 students in class
  - for each 10 students logging into the streaming server there are 7 fewer in class

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- We want to rationalise our three main findings: (1) low take-up, (2) homogeneous take-up by ability and (3) heterogeneous ITT/ATT on exam performance.
- Students optimally choose the mode of lecture attendance between **in-class**, **streaming** (if available) or **no attendance** (self study).
- The cost of class attendance is subject to shocks
  - with no shocks, class attendance is preferred
  - when the shock hits, the good students study at home, the less good still go to class
  - with streaming, they all stream but the counterfactuals are different

• Utility:

$$w_i(x_i, e_i) = x_i - \frac{e_i^2}{2} - c^j$$

• Learning technologies:

$$x_i = x^j(e_i) = \beta_i^{\gamma^j} e_i$$

with  $\beta_i \in (0, 1]$  and  $\gamma^n > \gamma^s \ge \gamma^a$ .

• Cost of adopting different learning technologies:

• 
$$c^s = c^n = 0$$
  
•  $c^a = \begin{cases} u \sim U[\underline{u}, \overline{u}] & \text{with probability } p \quad (\underline{u} > 0) \\ 0 & \text{with probability } 1 - p \end{cases}$ 

### Attendance choices - no streaming



### Attendance choices with streaming



# Implications of the theory

- Students of any ability level take up only when hit by shocks to the cost of in-class attendance
  - $\Rightarrow$  if the shocks are infrequent and serially uncorrelated, then the model predicts take-up compatible with our data
- When the shock hits and streaming is not available, the good students study on their own, the good students go to class
  - ⇒ when streaming is available, they all take up but the counterfactuals are different, thus leading to heterogeneous treatment effects

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- - Main results ٠
    - Students prefer traditional classroom lectures and use distance online 1 learning tools only when in-class attendance is too costly
    - Offering live streaming of classes is
      - beneficial for good students (counterfactual is no attendance)
      - ٠ detrimental for the less good students (counterfactual is class attendance)
  - Implications for education policy
    - Streaming lectures is unlikely to solve issues of overcrowding in the classrooms, at least in traditional institutions of higher education
    - Access to distance learning technologies should perhaps be offered based on merit

- Externalities/peer effects
- Use the model to derive strutural parameters about the relative efficiency of alternative attendance modes
  - perform policy simulations: stream all courses, improve efficiency of class attendance/streaming, et.
- Outcomes in non-streamed courses, both contemporaneous and subsequent courses.

## Instrumental variable estimates

Instrument <sup>b</sup> =	Dist. at enrolment <sup>c</sup>	Current distance <sup>c</sup>	Randomisation <sup>d</sup>
all students	-1.236	0.514	0.022
	(4.477)	(2.220)	(0.481)
F-stat 1st stage	3.3	20.5	454.1
By ability group	a		
Low	-2.741	-1.799	-0.638
	(3.264)	(2.726)	(0.936)
Mid	-2.559	0.429	-0.359
	(4.130)	(2.297)	(0.511)
High	1.993	5.060	1.598
	(4.827)	(4.371)	(0.804)
Obs. <sup>e</sup>	5153	5153	5153
Descriptive stat. of the dep. variable			
Mean	0.015	0.015	0.015
Sd	0.972	0.972	0.972