Disconnecting Women: Gender Disparities in the Impact of Online Instruction*

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Abstract

This paper examines gender disparities in the impact of online instruction. We randomly assign over 1,300 university students to different proportions of online and in-person lectures. Increased online instruction significantly reduces women's course performance but leaves men affected. The negative effect on women is concentrated in math-intensive courses. Online instruction in these courses also disproportionally lowers women's longer-term performance and likelihood of staying in their studies. Analyses of mechanisms suggest that women tend to prefer online lectures less and evaluate them as less informative, interactive, and accessible. Our findings highlight that shifting toward online instruction is particularly harmful for women.

Keywords: online instruction, gender disparities, field experiment
JEL Codes: J16, I23, C93

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1 Introduction

The rapid expansion of online education, accelerated by the Covid-19 pandemic, has reshaped the landscape of higher education. By 2024, 95.5% of post-secondary institutions in the U.S. offered some form of online instruction. Within these institutions, 40% of college administrators reported plans to increase spending on online education, compared to only 2% intending to reduce it.[1] While online education appeals for its flexibility and cost-effectiveness (Deming et al., 2015), it also substantially reduces the social and interactive elements of education. This can hamper students' motivation, comprehension, and sense of belonging, especially for those with interpersonal learning styles. Introducing online education also imposes greater challenges for students who are less engaged with digital technologies. While a growing body of literature highlights how "zooming to class" negatively impacts student performance (e.g., Figlio, Rush and Yin, 2013; Kofoed et al., 2024), this paper presents novel evidence that online instruction disproportionately harms women's short- and long-term educational outcomes.[2]

Why would online instruction affect men and women differently? A large literature documents gender gaps in how students learn and use technology. The "gender digital divide" describes the phenomenon that men and women differ in their access, use, and engagement with digital technology.[3] Compared to men, women are also more likely to be social learners (Arbaugh, 2000) and are more likely to rely on personal interactions with faculty and peers throughout the learning process (Kim and Sax, 2009; Wong and Chapman, 2023). The expansion of online education may therefore disadvantage women by reducing social interactions and increasing the reliance on digital tools.

In this paper, we examine how online instruction differentially affects the learning outcomes of men and women. We conduct a field experiment among 1,344 students enrolled in multiple courses at an international business school during the pandemic. To offer in-person learning opportunities while adhering to social distancing regulations, we conducted a "partial attendance" experiment during the first three weeks of fall semester in 2020. The experiment

[1] https://res.cloudinary.com/highereducation/image/upload/v1/BestColleges.com/2024_Online_Education_Trends_Report.pdf

[2] A couple of studies have highlighted that the Covid-19 pandemic can exacerbate inequality within and across regions (Jack and Oster, 2023) and that the effects of the pandemic can vary across families with different income levels or internet engagement (Bacher-Hicks, Goodman and Mulhern, 2021).

[3] Globally, 58% of men versus 48% of women report internet usage (ITU, 2019). Women are about 20 percentage points less likely than men to use ChatGPT, even when employed in the same occupation or studying the same subject (Humlum and Vestergaard, 2024). Men also tend to be more confident about their digital skills (Jackson et al., 2010; Li and Kirkup, 2007) and use the internet for solitary purposes, whereas women more often use it for socializing and communication (Weiser, 2000; Joiner, Stewart and Beaney, 2015; Tsai and Tsai, 2010).

allowed students to attend a random subset of lectures in person and the remaining lectures online. Due to the assignment, students were exposed to different proportions of online versus in-person lectures across courses. We exploit this within-student, cross-course variation to analyze how online instruction affects students' performance, learning experiences, and study persistence.

Our results show that being assigned to more online lectures has an overall negative effect on students' exam performance, consistent with most prior work. However, this overall effect masks large gender differences: While online instruction has no impact on men's exam performance, it substantially lowers women's performance. We find that increasing the proportion of online lectures by 10 percentage points lowers women's exam score by approximately 0.04 SD. For men, in contrast, we observe a precisely estimated null effect. The 95% confidence intervals allow us to rule out effects smaller than −0.01 SD and larger than 0.015 SD when men's assigned online share increases by 10 percentage points.

Could this gender gap in the impact of online instruction be a chance finding? Given that gender is a frequently observed and commonly tested characteristic, we must worry about reporting a statistically significant yet spurious gender gap. This concern is especially valid for the first paper documenting a stark gender difference in the effect of online instruction. To rule out the possibility of a false positive, we apply multiple testing corrections to all dimensions of heterogeneity that we preregistered. Applying the step-down procedure by Romano and Wolf (2005, 2016) results in a corrected p-value of 0.001 for the gender gap estimate (original p-value = 0.0002). A more conservative Bonferroni correction yields a p-value of 0.004. These results reject the idea that our findings are due to chance.

After establishing that online instruction significantly lowers women' course performance, we examine the dynamics of this effect by linking lecture content to individual exam questions. Specifically, we test how early exposure to online instruction affects student performance across various topics covered throughout the semester. Our results show that women exposed to more online lectures perform significantly worse for topics covered later in the semester. These dynamic spillovers suggest that online instruction undermines women's understanding of concepts that build on foundational knowledge, thus reducing their final exam performance.

To understand whether the teaching mode matters differently across courses, we examine heterogeneity of the effect by course. The results show that the negative effect of online instruction is concentrated in the relatively math-intensive courses, including "Mathematics" and "Microeconomics." A 10 percentage points increase in the proportion of online lectures in these courses lowers women's final course grades by approximately 0.08 SD—compared to

0.02 SD for other courses.

While our results clearly show that online instruction more adversely affects women's short-term performance, it is unclear whether these effects translate into longer-term disadvantages. We focus on online lectures in the math-intensive courses which strongly affect women's short-term performance.[4] The results show that online instruction in these courses disproportionally reduces women's credits earned during the first academic year and their likelihood of staying in their studies in the following years. These results highlight that online instruction has a meaningful and lasting negative influence on women's educational attainment.

Next, we examine *why* online instruction negatively affects women's performance, while leaving men's performance unaffected. We use survey and online lecture attendance data to explore two broad mechanisms: (1) gender differences in the preference for online lectures; and (2) gender differences in how online instruction affects learning experiences.

To understand preferences for online instruction, we survey students about their preferred teaching mode. We find that women are 36% less likely than men to report online instruction as their preferred mode. This gender difference is also reflected in lecture attendance behavior: Overall, women are less likely than men to attend online lectures, and this gender gap is substantially larger for lectures for which in-person attendance is permitted. This suggests that, whenever physical attendance is possible, women are more likely to attend in person—confirming their stronger preference for in-person instruction.

To understand students' learning experiences, we conduct an endline survey asking students to evaluate different course aspects. Three key results emerge: (1) Women exposed to more online lectures report lower overall course satisfaction. (2) These women tend to evaluate the lectures as less informative and clear. (3) They also report that the instructor was less engaging, and that it was harder to contact classmates for help. The effects for men are in the opposite direction and significantly different from women. Taken together, our results paint a consistent picture of why online instruction disproportionally harms women's learning outcomes: Online lectures hamper women from effectively understanding course content and getting feedback or help from instructors and peers.

This paper builds on a growing literature that has evaluated the impact of online education over the past decade (Bettinger et al., 2017; Coates et al., 2004; Xu and Jaggars, 2013; Figlio, Rush and Yin, 2013; Bowen et al., 2014; Joyce et al., 2015; Alpert, Couch and Harmon, 2016; Kofoed et al., 2024; Cacault et al., 2021; Alegría et al., 2023). Within this

[4]Although our analysis of short-term outcomes utilizes student-by-course level variations, the longer-term outcomes vary at the student level. This requires aggregating online exposure at the individual level. Therefore, we focus on variations in online lectures assigned in the math-intensive courses.

literature, only three papers report results split by gender, and none of them find significant gender differences in the effect of online instruction (Figlio, Rush and Yin, 2013; Bowen et al., 2014; Kofoed et al., 2024). Compared to our study involving a cohort of over 1,300 students across several courses, these prior studies examine a relatively small sample of students in a single Economics or Statistics course.[5]

Our study makes two main contributions to the literature. (1) We provide the first experimental evidence that online instruction disproportionately harms women. (2) We deliver comprehensive results on how online instruction affects short- and longer-term educational attainment, attendance behaviors, and learning experiences. While previous studies have looked at the contemporaneous effects of online education, we provide novel evidence on longer-term effects and potential mechanisms underlying the impact of online education. In our male-dominated business school setting, men consistently outperform women. Our finding that online education affects students differently by gender raises important concerns about its potential to exacerbate gender inequalities. While online education offers greater accessibility and flexibility, it appears to do so at the expense of reducing women's engagement, satisfaction, and preparedness for future academic challenges.

More broadly, our study echos rich economics and education research that examines gender differences in preferences or behaviors in learning and working settings. Prior studies find that women benefit more than men from interactive and collaborative learning environments (Belenky et al., 1988; Klein et al., 1994; Arbaugh, 2000; Zhu, 2012); women have lower propensity to use technologies (Carvajal, Franco and Isaksson, 2024; Humlum and Vestergaard, 2024); women tend to earn less on online working platforms (Litman et al., 2020; Cook et al., 2021; Adams-Prassl et al., 2023); and women gain more from proximity to team members in the workplace (Emanuel, Harrington and Pallais, 2023). We complement prior work by documenting that women hold a stronger preference for in-person instruction and benefit more from interactive, face-to-face teaching environments.

2 The Experiment

Background: The setting of our experiment is an international business school at a European research university. Each year, more than 1,000 students enroll in the business school with a declared major or minor study program related to business, economics, finance, or informatics. To remain in the major program, students have to pass a series of mandatory

[5]Specifically, Bowen et al. (2014) include a sample of 605 students in a Statistics course; Figlio, Rush and Yin (2013) and Kofoed et al. (2024) include a sample of 327 and 551 students, respectively, in an Economics course.

courses. Our experiment includes four of these mandatory courses that students primarily take in the first semester of their study: Microeconomics (9 credits); Mathematics (6 credits); Financial Accounting (6 credits); and Business Administration (3 credits).

In the spring semester of the 2019/20 academic year, the Covid-19 pandemic broke out. As a result, the university had to abruptly switch to online instruction. However, given the low infection rate during the summer of 2020, the university decided to restore in-person instruction in the fall of 2020, subject to social distancing regulations. In collaboration with the business school, we conducted a "partial attendance" experiment that allowed students to attend a random subset of lectures in person.[6]

"Partial attendance" experiment: In this experiment, all students enrolled in the business school were randomly assigned into five in-person attendance groups (Group A to Group E), according to the last digit of student ID—the last digit is a random number ranging from 0 to 9. Meanwhile, we divided an instruction week into five blocks with similar presence of courses. Finally, we allocated the five attendance groups to the five teaching blocks, and students were only permitted to physically attend the lectures within their assigned block. This design ensured that only 20% of students were allowed to come to campus simultaneously, thus adhering to social distancing rules. Figure 1(a) shows the weekly timetable, how it was divided into five teaching blocks, and the scheduled times for the four courses.

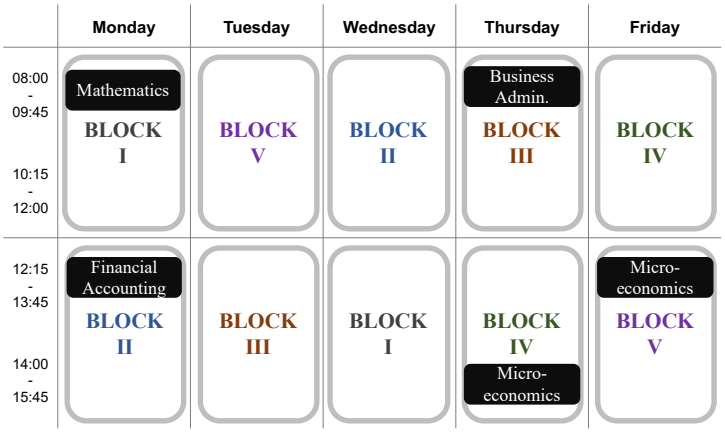
In addition, we rotated the attendance groups through different teaching blocks week by week, so that students got exposed to in-person instruction in different courses. Figure 1(b) shows how the five attendance groups were assigned to five teaching blocks, from week 1 to week 3. Following the rotating schedule, students in Group A were permitted to physically attend courses scheduled in Block I (Mathematics) in week 1, courses in Block II (Financial Accounting) in week 2, and courses in Block III (Business Administration) in week 3. Students in Group B can physically attend Financial Accounting in week 1, Business Administration in week 2, and Microeconomics in week 3. Similarly, one can infer from the schedule which courses students in Groups C, D, and E were permitted to attend in person in different weeks.[7]

[6]The experiment conducted for this paper received IRB approval from the University of Zurich and was registered as AEARCTR-0006538.

[7]The timetable also includes other courses, depending on students' study program and year of study. Almost all courses offered at the business school had to follow the assigned rotating schedule: in-person attendance was only permitted for certain students in designated weeks. However, many instructors decided to deliver their course purely or primarily online. Therefore, we focus our analysis on the four large compulsory courses that strictly followed the partial attendance schedule.

Figure 1. The Weekly Timetable and the Schedule for In-Person Attendance

(a) Teaching Blocks and Courses



(b) In-Person Attendance Schedule

Teaching Block (I–V)	Attendance Group (A–E)					
	A	B	C	D	E	
	I	II	III	IV	V	(Week 1)
	II	III	IV	V	I	(Week 2)
	III	IV	V	I	II	(Week 3)

Notes: Figure (a) shows the timetable of an instruction week and the scheduled times of four courses in our sample: Mathematics, Financial Accounting, Business Administration, and Microeconomics. Figure (b) shows which teaching blocks students in each attendance group were allocated to from week 1 to week 3. When assigned to a teaching block, students were permitted to physically attend courses in the block. For example, students in Group A can physically attend courses in Block I in week 1, courses in Block II in week 2, and courses in Block III in week 3.

Although the partial attendance experiment was designed to cover the whole fall semester, it lasted only for three weeks due to unexpected changes in university policies and the Covid-19 pandemic. From week 4, the university relaxed restrictions on in-person instruction given the low infection rate during the past weeks. However, the Covid situation rapidly deteriorated, and the university had to abandon all in-person instruction from week 7. All teaching, as well as all final exams, were administered online during the rest of the semester. Appendix Figure A.1 shows a timeline of our experiment and the Covid situation.

Variations in online instruction: As a result of the partial attendance experiment, students were exposed to different proportions of online versus in-person lectures across courses during the first three weeks of the semester. For example, students in Group A were permitted to physically attend one of three lectures in the Mathematics, Financial Accounting, and Business Administration courses but were assigned to attend the Microeconomics course fully online. By contrast, students in Group D were allowed to attend 2 of 6 Microeconomics lectures in person but had to attend Financial Accounting and Business Administration fully online.

Given these rich within-student, cross-course variations in the fraction of online (versus in-person) instruction, we are able to examine how exposure to online instruction influences students' exam performance, learning experiences, and even longer-run achievement. Among

our analysis sample of 3,770 student-by-course observations, the proportion of online lectures ranges from 66.7% to 100%, with an average value of 80%.

3 Data and Descriptive Statistics

We use rich administrative data from the university, complemented by lecture attendance and survey data, to estimate the impact of online instruction and explore the underlying mechanisms. We describe the different sets of data as follows.

Registration and exam data: We acquire the following data from course administrators for each course: demographic and educational backgrounds of each enrolled student, including gender (either female or male), age, nationality, major, and home address registered before the start of the semester;[8] students' obtained total score in the final exam, which ranges from 0 to 120; the original questions used in the exam (mostly multiple-choice questions) and students' obtained points for each question, which range from -1.5 to 4; and the final grade for the course, which ranges from 1 to 6 (1 as the lowest grade and 4 as the passing grade).

In this paper, we primarily use the obtained total exam score as the measure of course performance, since it captures more granular variations. To test robustness of our results, we use the final grade and course passing indicator as alternative measures of performance. To unpack the overall impact of online instruction on course-level performance, we further use question-level data to analyze potential dynamic effects of online instruction (see Section 5.3).

Zoom attendance data: To explore students' lecture attendance behaviors under different conditions, we use the recorded lists of attendants for online Zoom lectures of the Microeconomics course: the largest assessment course taken by most students in our sample. We will use the data to compare students' online attendance rate when in-person attendance is allowed and not allowed.[9] Although the data is only available for one course, it helps to unveil systematic differences in students' preferences for online or in-person lectures (see Section 6 for details).

[8] We use the home address to calculate the commute time from home to campus. Note that the home address may change after the semester starts, so our measure of communte time may be inaccurate for some students.

[9] Our attendance data only covers the period of week 1 to week 7 of the semester, given that all teaching in the university were shifted online after in the later period.

Baseline survey data: In addition to the course registration data that capture various background characteristics of students, we conducted a baseline survey among students enrolled in the Microeconomics course. The survey measures students' personality traits, high school grades, and study habits, with an overall response rate of 85%. Although the data are not available for all students in our sample, we mainly use them for heterogeneity analyses in Section 5.2—our main analyses will control for student fixed effects.

Endline survey data: We also conducted an endline survey at the end of the semester among all students. In this survey, we elicit students' preferences for different teaching modes, evaluations of different courses, and their learning experiences in different courses. The response rate for the survey is relatively low (45%), but the data provides suggestive evidence on the underlying mechanisms for the effect of online or in-person instruction (see Section 6).

Table 1 presents descriptive statistics of the student population (Panel A) and their exam performance (Panel B). Among the 1,344 students in the sample, 41% of them are female; their average age is 21; 16% of them are international students (i.e., foreign nationals); and students' median commute time from home to the campus is 36 minutes. In terms of the study programs, 57% of students are enrolled in a major related to business, economics, or finance—students in these majors have the same set of assessment courses; 18.5% are enrolled in a major related to informatics at the business school; and the remaining 25% have other majors in other faculty but are enrolled in a minor program at the business school.

In addition to these characteristics observed in the administrative registration data, the baseline survey provides other background characteristics of students. Panel A of Table 1 shows that for the 892 students who have answered the survey, their average high school final grade for math and first language is 4.7 (on a scale of 1 to 6). Students also report their study hours in high school when studying alone and with others: We use the proportion of hours studying alone (67% on average) as the measure self-study intensity. The survey also measures students' general tendency for group study with the following questions: "Working together with other students helps me to understand the subject matter;" "I am good at explaining things to other people;" and "Learning on my own is more effective than working with others" (reversed). Students report to what extent these statements apply to them on a Likert scale of 1 (does not apply at all) to 7 (applies perfectly), and we use the average agreement score to capture group study preference. Finally, we also elicit students' conscientiousness and extraversion using questions from the Short 15-item Big Five Inventory (Gerlitz and Schupp, 2005).

Table 1. Descriptive Statistics

	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Panel A: Student Characteristics					
Male	1,344	0.592	0.492	0	1
Age	1,344	21.33	2.551	18	41
International Student	1,344	0.157	0.364	0	1
Commute Time to University (minutes)	1,344	38.07	36.31	4.3	600.5
Business/Economics/Finance Majors	1,344	0.57	0.495	0	1
Informatics Majors	1,344	0.185	0.388	0	1
Other Majors	1,344	0.246	0.431	0	1
High School Grade	892	4.663	0.512	2.75	6
High School Self-Study Intensity	880	0.670	0.201	0	1
Group Study Preference	892	4.256	0.93	1	7
Conscientiousness	892	4.796	0.955	1	7
Extraversion	892	4.747	1.244	1	7
Panel B: Exam Performance					
Total Course-Level Score	3,770	34.2	18.89	0	106
Question-Level Points	117,499	1.095	1.372	-1.5	4

Notes: The table shows summary statistics for students' background characteristics and their performance outcomes at the course level or exam question level. For each variable, we show the number of observations (N), the mean value, the standard deviation (SD), and the minimum and maximum values. Student characteristics observed for all 1,344 students are derived from administrative data; other variables are derived from a baseline survey with 892 respondents. *High School Grade* refers to the average final math and language grade in high school. *High School Self-Study Intensity* refers to the proportion of study hours spent alone (versus with other students)—the variable is missing for several students due to invalid responses. Appendix Table B.1 shows the summary statistics separately for men and women.

4 Estimation Strategy

We primarily use the within-student cross-course variations in the exposure to online instruction at the start of the semester to estimate the impact of online instruction on learning outcomes. Below is our preferred model to estimate this impact (and the gender difference in this impact):

$$Y_{ic} = \alpha_i + \sigma_c + \beta \cdot Online_{ic} \ (+ \ \gamma \cdot Female_i \times Online_{ic}) + \varepsilon_{ic}. \tag{1}$$

In this specification, the outcome variable (Y_{ic}) is the total exam score obtained by student i in course c. The term α_i captures all student-level variations in the outcome, and the term σ_c captures all course-level variations. The key variable of interest, $Online_{ic}$, captures the exposure of student i to online instruction in course c (i.e., the proportion of lectures assigned to be online). ε_{ic} is the error term. Since we observe multiple courses per student, we cluster standard errors at the student level. The inference results are very similar when we cluster

standard errors at the student-by-course level.

To examine the gender difference in the impact of online instruction, we additionally include the interaction term between $Online_{ic}$ and an indicator for female students ($Female_i$). In this case, β estimates the impact of online instruction on men, and γ estimates the gender gap in the impact. Without the interaction term, β simply estimates the combined impact of online instruction on all students. For robustness, we also split the sample by gender and estimate the effect of online instruction separately for the sample of men and women.

Table 2. Balance Tests

(1)	(2)	(3)	(4)	(5)
	A. Effect of % Online Lectures		B. Joint Significance of Attendance Groups	
Dependent Variable	Coefficient	S.E.	F-statistic	p-value
Male	-0.018	(0.029)	0.419	0.795
Age	-0.195	(0.136)	1.972	0.096
International Student	0.003	(0.020)	1.110	0.350
Business/Economics/Finance Majors	0.004	(0.031)	0.248	0.911
Informatics Majors	0.003	(0.020)	0.640	0.634
Other Majors	-0.007	(0.031)	0.303	0.876
Commute Time to University (min.)	0.549	(1.727)	0.199	0.939
High School Grade	-0.018	(0.029)	1.085	0.363
High School Self-study Intensity	-0.005	(0.011)	1.918	0.105
Group Study Preference	-0.043	(0.053)	1.578	0.178
Conscientiousness	-0.005	(0.055)	0.668	0.614
Extraversion	-0.063	(0.071)	0.757	0.554

Notes: Panel A tests whether the proportion of online lectures significantly predicts baseline characteristics. Each point estimate is derived from one OLS regression. In all regressions, we control for course fixed effects and cluster standard errors at the student level. The estimated coefficients and standard errors (S.E., in parentheses) are in Columns (2)–(3). Panel B tests whether students are randomly assigned into five attendance groups. Specifically, for each baseline characteristic, we test the joint significance of four teaching group dummies (one group omitted) in predicting the characteristic. The F-statistics and p-values derived from the tests are in Columns (4)–(5).

The key identification assumption for the estimation is that the exposure to online instruction is exogenous and uncorrelated to other factors in the error term that may affect learning outcomes. This is guaranteed through the experiment since students are randomly allocated to different attendance groups with varying timing of online and in-person lectures. To confirm that the randomization was successful and the variations we analyze are exogenous, we conduct two balance tests. First, we directly test whether student characteristics at baseline significantly vary with the proportion of online instruction. We find no such evidence, as Table 2, Panel A shows. Second, we test whether student characteristics are balanced across five attendance groups (Groups A to E). The results in Table 2, Panel B, show that only one out of 12 student attributes at baseline appears

marginally predicted by the attendance group dummies. Altogether, we find convincing evidence that our randomization was successful.[10]

5 Results

5.1 Estimating the Impact of Online Instruction

Table 3, Columns (1)–(3), present the overall impact of online instruction on course performance, estimated with 3,770 student-by-course observations. Course performance is measured with the obtained total exam score, which is standardized across the whole sample to have a mean of 0 and SD of 1.

Table 3. The Impact of Online Instruction on Course Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Standardized Exam Score					
% Online Lectures	-0.103**	-0.101**	-0.130**	-0.326***	-0.311***	-0.379***
	(0.051)	(0.051)	(0.053)	(0.080)	(0.079)	(0.085)
	[0.043]	[0.048]	[0.014]	[0.000]	[0.000]	[0.000]
% Online Lectures × Male				0.373***	0.350***	0.409***
				(0.103)	(0.103)	(0.108)
				[0.000]	[0.001]	[0.000]
Male		0.158***		-0.182**	-0.122	
		(0.034)		(0.090)	(0.090)	
Age		-0.024***			-0.024***	
		(0.007)			(0.007)	
International Student		-0.212***			-0.212***	
		(0.044)			(0.044)	
log(Commute Time)		-0.078***			-0.078***	
		(0.022)			(0.021)	
Observations	3,770	3,770	3,488	3,770	3,770	3,488
R-squared	0.519	0.549	0.838	0.523	0.549	0.839
Course Fixed Effects	✓	✓	✓	✓	✓	✓
Major Category Fixed Effects		✓	-		✓	-
Student Fixed Effects			✓			✓

Notes: The table shows the estimated impact of online instruction on students' course performance. Each column represents one Ordinary Least Squares (OLS) regression. The dependent variable is students' total exam score obtained for different courses, standardized across the whole sample to have a mean of 0 and a SD of 1. The key variable of interest is the proportion (%) of lectures assigned to be online. Standard errors in parentheses are clustered at the student level. p-values are in brackets. *p <.1, **p <.05, ***p <.01.

[10] Appendix Table B.2 further tests whether the online proportion predicts baseline characteristics, separately for men and women. For female students, we find that none of the baseline characteristics are predicted by online instruction. For male students, only age is significantly predicted by the proportion of online lectures, but this could be a chance finding. Our estimation results in the paper are robust to controlling for these characteristics and even student fixed effects.

The results show that increasing exposure to online instruction has an overall negative effect on students' course performance. When only controlling for course fixed effects (in Column 1), we find that increasing the online proportion by 100 percentage points (1 unit) reduces the exam score by 0.1 SD (p-value = 0.043). The estimated effect remains statistically significant at the 5% level and has a similar magnitude when additionally controlling for student characteristics such as gender, age, international status, commute time, and major (see Column 2). When including both course fixed effects and student fixed effects, our preferred specification, the results are similar and even become more precisely estimated (see Column 3). Using this specification, we find that increasing the proportion of online lectures by 1 unit reduces exam score by 0.13 SD. This means that increasing online proportion from 66.7% to 100%—the actual range of variation—has a negative effect of 0.043 SD.

How large is this effect? Compared to previous experimental studies in the literature, our estimated overall effect is comparable but relatively moderate. For example, Kofoed et al. (2024) find that students assigned to (100%) online instruction obtain course grades lower by about 0.21 SD than students assigned to (100%) in-person instruction. Using similar comparisons, Figlio, Rush and Yin (2013) find that a 100 percentage points increase in online instruction lowers students' exam score by about 0.20 SD.

Gender gap in the impact: Table 3, Columns (4)–(6), present the estimated gender gap in the impact of online instruction. The results show that online instruction has a substantial negative effect on women's exam performance (see the coefficient of "*% Online Lectures*"). As the assigned proportion of online lectures increases by 10 percentage points, women's final exam score decreases by approximately 0.035 SD, an effect precisely estimated (p-value < 0.001). The results also show that the effect of online instruction on men's performance is significantly larger and close to zero in value—see the coefficient of the interaction term "*% Online Lectures* $\times$ *Male*". This gender gap is estimated with great precision (p-value ≤ 0.001) and remains robust across specifications.

Split-sample analysis: To make sure that the estimated gender gap in Table 3 is not driven by potential interaction effects between gender and other factors (the fixed effects or unobservables in the error term), we further split the sample by gender and separately estimate the impact of online instruction. Table 4 presents the results, with Panel A focusing on female students and Panel B focusing on male students.

Columns (1)–(3) show that female students exposed to more online lectures obtain significantly worse performance in the final exam. As the proportion of online lectures increases by 10 percentage points, their exam score decreases by 0.038 SD, according to

the specification with student fixed effects. The 95% confidence interval of this effect is [−0.05, −0.02] SD and is almost identical when standard errors are clustered at the student-by-course level (S.E. in curly brackets). By contrast, Columns (4)–(6) show that online instruction has no impact on male students' course performance. The estimated effect is close to zero and also precisely estimated. For example, when controlling for student fixed effects, increasing the proportion of online lectures by 10 percentage points is estimated to increase men's exam score by 0.003 SD, with the 95% confidence interval ranging from −0.001 to 0.015 SD. Collectively, these results provide consistent evidence that online instruction disproportionally harms women's performance compared to men.

Table 4. The Impact of Online Instruction by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Female Students			Male Students		
% Online Lectures	-0.328***	-0.316***	-0.379***	0.049	0.038	0.030
	(0.079)	(0.078)	(0.084)	(0.066)	(0.067)	(0.068)
	{0.106}	{0.104}	{0.089}	{0.089}	{0.087}	{0.070}
Course Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	–	No	Yes	–
Student Fixed Effects	No	No	Yes	No	No	Yes
Observations	1,502	1,502	1,401	2,268	2,268	2,087
R-squared	0.549	0.569	0.841	0.506	0.538	0.837

Notes: The table shows the estimated impact of online instruction on the performance of women and women. The dependent variable is the total exam score standardized across the whole sample. In Columns (2) and (5), the specifications include the same set of student controls as in Column (3) of Table 3. Standard errors in parentheses are clustered at the student level; standard errors in curly brackets are clustered at the student-by-course level. $^{*}p$ <.1, $^{**}p$ <.05, $^{***}p$ <.01.

Other performance outcomes: Although the total exam score captures detailed variations in performance, one may wonder whether the impact on exam score translates into changes in final course grade and the likelihood of passing the course, which are relevant margins of performance for students. In Appendix Table B.3, we show the estimated effects of online instruction on course grade and the pass rate separately for women and men. The results reveal consistent patterns: Women assigned to more online lectures in a course obtain lower final grade and become less likely to pass the course. Specifically, as the proportion of online lectures increases from 67% to 100%, women's course grade decrease by 0.15 SD, and their course pass rate decreases by 0.07 percentage points. Both of these estimates are statistically significant at the 1% level. Similarly, we find no significant impact of online instruction on men's final grade or course pass rate.

5.2 Heterogeneity by Other Student Attributes

Our results above reveal a large and significant gender gap in the impact of online instruction. In our pre-registration of the experiment, we also specified other dimensions of sub-group analysis: gender, previous achievement, nationality, self-study habits, group study preference, conscientiousness, extraversion, commute time, and major. We acquire these student characteristics either from the administrative data (observable for all students) or from the baseline survey (for 85% of the sample). To test for heterogeneity, we divide students into two subsamples (as we pre-registered) and estimate the effects of online instruction on the performance of students in two samples using a fully interacted model. We further test the difference in the effect along each dimension.[11]

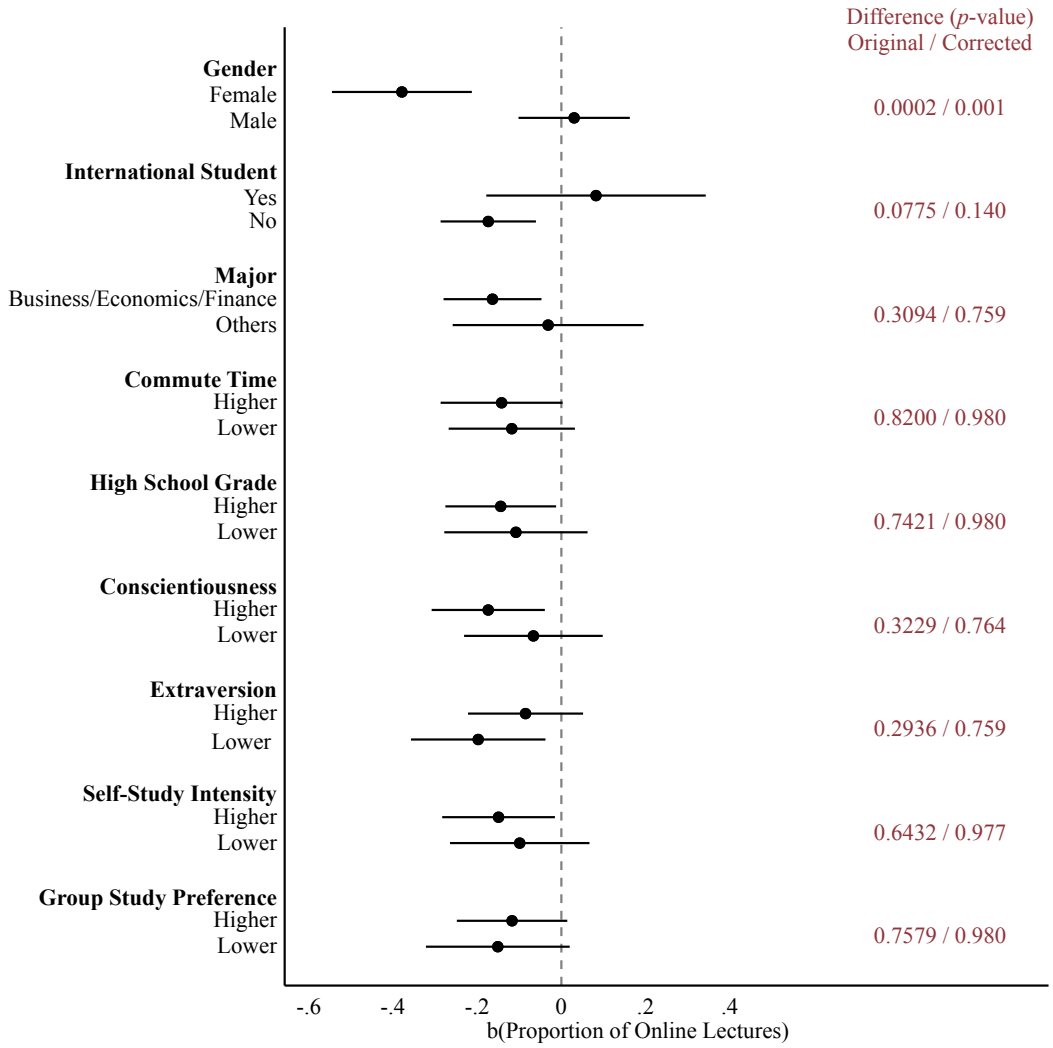
Figure 2 shows estimated effects of online instruction on various sub-samples of students, as well as the p-values derived from the tests of difference in impact. We find that most of the point estimates are negative in direction, albeit with varying precision. Interestingly, except for the gender gap, the differences in the impact by all other student attributes do not reach statistical significance at the 5% level.

Multiple testing correction: Since we examine heterogeneity along various dimensions, we need to account for multiple hypotheses testing and adjust the inference results accordingly. To that end, we apply the step-wise multiple testing approach of Romano and Wolf (2005) that controls family-wise error rate simultaneously to the 18 estimators of 9 models. Each model includes the online instruction variable and its interaction with a student attribute.[12] We show the corrected p-values for the estimated differences in Figure 2 (see Appendix Table B.4 for the original 18 estimates, together with the corrected p-values). We find that while the gender gap in the effect of online instruction remains statistically significant after correction (corrected p-value = 0.001), none of the differences along other dimensions survives the correction. The gender gap remains statistically significant even when applying the most conservative Bonferroni correction (corrected p-value = 0.0036). Taken together, our results provide convincing evidence that the gender difference in the effect of online instruction is a robust finding and unlikely represents false positive.

[11] Specifically, the model includes two interaction terms, between the online proportion and each of the two subsample indicators, controlling for course fixed effects and student fixed effects.

[12] We use the procedure of Romano and Wolf (2016) by resampling 1,000 student-clusters (each student has multiple observations) within the five strata of assigned attendance groups.

Figure 2. Heterogeneity of the Impact by Different Student Attributes



Notes: The figure shows the estimated effects of online instruction on different sub-samples of students, divided based on their background characteristics. For continuous characteristics such as commute time and conscientiousness, the "Higher" group refers to students with above-median levels of the characteristic. For each characteristic, we use a model with two interaction terms (between online instruction and two subsample indicators), controlling for course fixed effects and student fixed effects. We cluster standard errors at the student level; the error bars indicate 95% confidence intervals. We then test the difference between the two interaction terms and report the p-values. Finally, we apply the Romano-Wolf multiple testing correction to all estimates and report the corrected the p-values for the between-group differences.

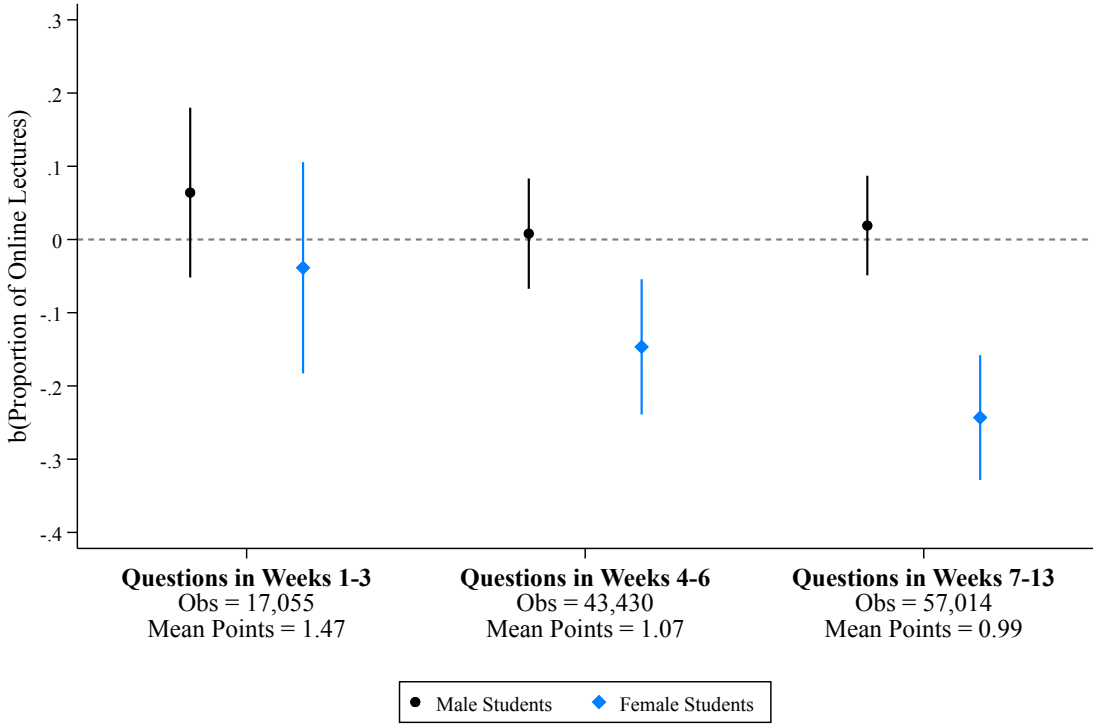
5.3 Dynamic Spillover Effects

The results above establish that increased exposure to online lectures at the start of the semester significantly lowers women's course performance, while leaving men's performance unaffected. It remains unclear how online instruction can influence the final performance at the end of the semester. Is it simply because women learn the early course content less

effectively? Or is it because the early online instruction hampers women's learning efficacy throughout the semester?

We try to unpack this impact by breaking down the overall performance into performance related to course content covered in different periods of the semester. Specifically, we manually code when the topic of an exam question is covered in a course by mapping exam questions to different lectures and splitting them into three periods: questions covered in weeks 1 to 3 of the semester, questions covered in weeks 4 to 6, and those covered in weeks 7 to 13. Then, we separately estimate the effects of early online instruction on the obtained points for questions covered in different periods. Figure 3 shows the estimated effects for men and women, using a total of 117,499 student-question-level observations.

Figure 3. The Impact of Early Online Instruction on Exam Performance by Period



Notes: The figure shows the estimated effect of the proportion of online lectures in the obtained points for exam questions covered in weeks 1–3, 4–6, and 7–13, respectively. The dependent variable, the obtained exam points on a scale of −1.5 to 4, is standardized separately for each period to have a mean of 0 and a SD of 1. The two estimates for each period are derived from one regression that includes two interactions terms: *%Online* × *Female* and *%Online* × *Male*. The regressions control for student fixed effects and question fixed effects and cluster standard errors at the student-by-question level. For female students, the first point estimate is not statistically different from the second point estimate (p-value = 0.23) but is statistically different from the third point estimate (p-value = 0.02). When combining questions in weeks 1 to 6, the impact on these questions is significantly different from the impact on questions in weeks 7–13 (p-value = 0.041). Similarly, when combining questions in weeks 4 to 13, the impact on these questions is significantly different from the impact on questions in weeks 1 to 3 (p-value = 0.047). The gender difference in the impact is statistically significant in period 2 (p-value = 0.013) and period 3 (p-value < 0.001).

The results show that for questions covered in the first three weeks of the semester, the proportion of online lectures in this period has a directionally positive effect on men's performance and negative effect on women's performance. However, neither effect is statistically significant. For questions covered in later periods of the semester, we find that early exposure to online instruction significantly lowers women's performance but has no impact on men's performance. Interestingly, while the null effect on men is dynamically stable, the negative effect of early online instruction becomes increasingly strong over time. As the proportion of online lectures in the first period increases from 67% to 100%, women's obtained points for questions in this period decrease by 0.017 SD (insignificant), their points for questions in weeks 4–6 decrease by 0.05 SD, and their points for questions in weeks 7–13 decrease by 0.08 SD. These strong dynamic spillover effects suggest that early exposure to online instruction hampers women's learning efficacy for later course content.

To understand the dynamic spillover effect, we may refer to the concept of "cumulative learning" in that knowledge and skills are accumulated gradually (Maton, 2009; Seel, 2011). As Figure 3 summarizes, the average obtained points are relatively higher for the questions covered in weeks 1 to 3, suggesting that the early lectures likely cover basic concepts of a course. If women are not used to online learning or learn less well remotely, being assigned to more online lectures in the beginning of a semester may hinder women from establishing a solid foundation for more advanced topics covered later in the semester. Although this negative effect of online lectures is not evident for the basic and easy questions, it is clearly revealed by the worse performance on more advanced and difficult questions.

5.4 Impact of Online Instruction by Course

Our results above show that online instruction is differentially detrimental for women compared to men, and there is no systematic heterogeneity of the impact by other student characteristics. Next, we examine whether the effect of online instruction varies across courses that may differ in the content, instructor characteristics, and teaching styles.

Table 5 shows the estimated impact of online instruction on female students' performance by course. When focusing on the obtained exam score, we find that online instruction has the most pronounced effect on women's performance in the Microeconomics course, followed by Mathematics (see Columns 1–2). When measuring performance with final course grade, we find that online instruction significantly and similarly reduces women's performance in Microeconomics and Mathematics (see Columns 3–4). Consistently, we find no significant impact of online instruction on women's performance in Business Administration or Financial Accounting.

Table 5. The Impact of Online Instruction on Women's Performance by Course

	(1)	(2)	(3)	(4)
	Standardized Exam Score		Standardized Course Grade	
% Online Lectures × Microecomics	-1.006***	-0.992***	-0.774*	-0.747**
	(0.364)	(0.306)	(0.411)	(0.355)
% Online Lectures × Mathematics	-0.481***	-0.334*	-1.094***	-0.829***
	(0.169)	(0.194)	(0.334)	(0.276)
% Online Lectures × Financial Accounting	-0.009	-0.094	-0.049	-0.217
	(0.222)	(0.177)	(0.289)	(0.258)
% Online Lectures × Business Administration	-0.053	-0.152	-0.038	-0.140
	(0.124)	(0.162)	(0.257)	(0.245)
Observations	1,502	1,401	1,502	1,401
R-squared	0.552	0.843	0.096	0.726
Course Fixed Effects	✓	✓	✓	✓
Student Fixed Effects		✓		✓

Notes: The table shows the estimated impact of online instruction on students' performance in four courses. The outcome variable is the standardized exam score in Columns (1)–(2) and the standardized course grade in Columns (3)–(4). Each column represents one OLS regression that controls for course fixed effects (and student fixed effects). Standard errors in parentheses are clustered at the student level. The p-values in the last four rows are derived from tests of differences between the interaction terms within each column. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Why is online instruction particularly harmful for women's performance in the relatively math-intensive and quantitative courses than in the other courses? It could be due to women learning math materials better in person than remotely. It could also be because the instructors of the economics and math courses are more engaging, so that women benefit more from the in-person learning experience. Although we cannot pin down why the effect varies across courses, our results provide valuable evidence that the impact of online instruction may depend on the setting.[13]

5.5 The Longer-Term Impact on Educational Attainment

Our analyses thus far focus on course performance in the short term, since we use variations in online instruction across courses. One may wonder whether online instruction in different courses also influences students' longer-term educational outcomes. For example, if a student is assigned to more online lectures in the math-intensive courses, the learning loss may accumulate and adversely affect achievement in the long run.

To examine potential longer-term effects, we acquire administrative data from the business school to capture three proxies for academic achievement and persistence: (1) the share

[13]The heterogeneity cannot be simply be explained by the instructor's gender, as only the math course is taught by a female instructor.

of course credits that students earned in the 2020/21 academic year (i.e., the quotient of earned credits by booked credits); (2) remaining enrolled at the business school in the fall semester of the 2021/22 academic year; and (3) remaining enrolled in the spring semester of the 2021/22 academic year. To reduce the dimension of analysis, we create an inverse covariance weighted index of educational attainment that combines these three proxies, following the method of Anderson (2008). Note that the long-term attainment is measured at the student-level (instead of student-by-course level). Therefore, we can only estimate the effects of online instruction in a specific course or a combination of courses.

Guided by our findings in Section 5.4, we focus on the Microeconomics and Mathematics courses and estimate how the average exposure to online instruction in these courses affects students' educational attainment in the longer term.[14] Column (1) of Table 6 shows that overall, increased exposure to online instruction in the math-intensive courses appears to decrease women's longer-run attainment but raises men's attainment. Considering that the follow-up enrollment and course registration decisions may be confounded by various factors for students in higher years of their program, we further limit our analysis to first-year students. When focusing on these students, the estimated overall impact is similar (see Column 2): As the average proportion of online lectures in Microeconomics and Mathematics increases by 10 percentage points, women's longer-run attainment index decreases by 0.14 SD, while men's attainment increases by by about 0.06 SD—the gender gap in the impact is statistically significant at the 5% level.[15]

When breaking down the overall attainment index into its three components, we find similar effects of online instruction for all components (see Columns 3–5). Women who are exposed to more online lectures in the math-intensive courses appear to earn a lower fraction of credits in the 2020/21 academic year and become less likely to remain enrolled in the business school in the fall semester and spring semester of the 2021/22 academic year. Consistently, the estimated effects of online instruction in math-intensive courses on men's longer-term outcomes are significantly higher in value.

[14]Note that we cannot simultaneously estimate the effects of online instruction in different courses because the exposure is correlated across courses. For example, given that Mathematics and Microeconomics are scheduled on Monday, Thursday, and Friday and that Business Administration and Financial Accounting are scheduled on Tuesday and Wednesday, students who are exposed to more online lectures in Mathematics and Microeconomics naturally have fewer online lectures in the other two courses. The average proportion of online lectures in these two pairs of courses has a correlation coefficient of −0.75.

[15]In Appendix Table B.5, we show how online instruction in each of the four assessment courses separately affects the longer-run attainment of first-year students. The results show that exposure to online instruction in the Mathematics course has a particularly negative impact on women's attainment, and its impact on men's attainment is significantly higher. By contrast, exposure to online versus in-person instruction in other three courses do not significantly affects students' educational outcomes in the longer term.

Table 6. The Long-Term Impact of Online Instruction in Math-Intensive Courses

	(1)	(2)	(3)	(4)	(5)
	All	First-Year Students			
	Standardized Overall Index		% Credits Earned 2020/21	Enrolled Fall 2021	Enrolled Spring 2022
% Online in Micro/Math	-1.039	-1.390*	-0.366	-0.570*	-0.593*
	(0.674)	(0.740)	(0.225)	(0.320)	(0.341)
% Online in Micro/Math × Male	1.679**	1.957**	0.524*	0.790**	0.835**
	(0.837)	(0.900)	(0.284)	(0.379)	(0.413)
Male	-1.074	-1.349*	-0.374*	-0.532*	-0.566*
	(0.668)	(0.717)	(0.226)	(0.303)	(0.330)
Observations	835	734	734	734	734
R-squared	0.109	0.084	0.088	0.057	0.074
Mean Dep. Var.	0	0.068	0.714	0.813	0.734

Notes: The table shows the effects of online instruction in Microeconomics and Mathematics on students' longer-term educational attainment. The key variable of interest is the average proportion of online lectures in Microeconomics and Mathematics; it varies from 67% to 92%. The dependent variable in Columns (1)–(2) is a standardized Anderson index created based on three specific outcomes (in Columns 3–5): the share of credits earned in 2020/21, being enrolled at the business school in the fall semester of 2021, and being enrolled in the spring semester of 2022. The sample in Column (1) includes all students who take both the Microeconomics and Mathematics courses; Columns (2)–(5) focus on the first-year students in our sample. Each column represent one OLS regression, in which we control for nationality, age, major, and commute time. Robust standard errors are in parentheses. The inference results are very similar when we use HC2, HC3, Boostrap, or Jackknife standard errors. $^{*}p<.1$, $^{**}p<.05$, $^{***}p<.01$.

6 Possible Mechanisms

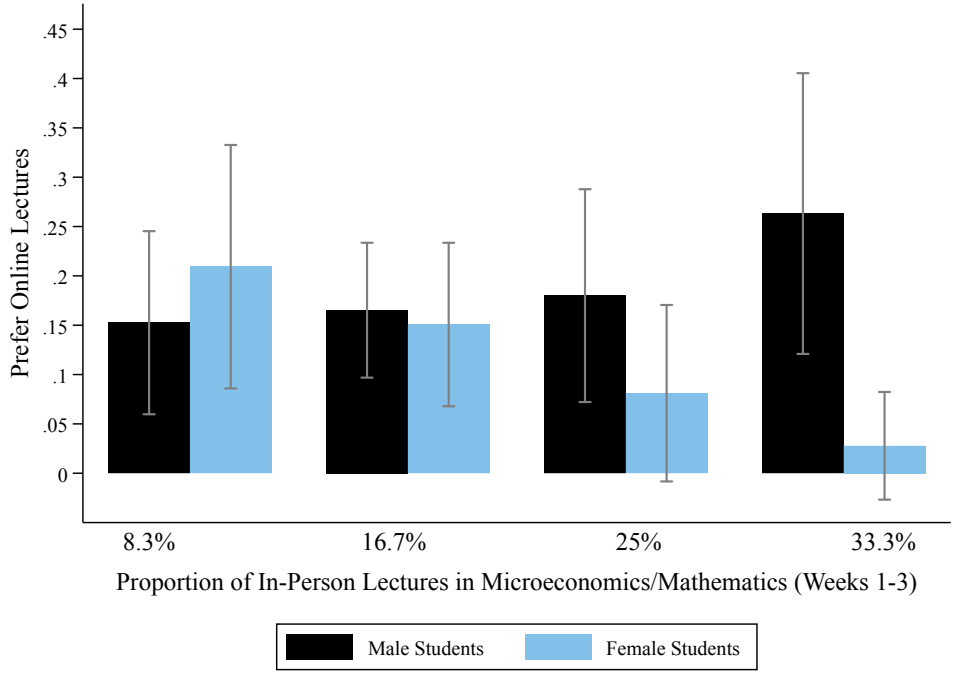
Our results so far establish a clear gender gap in the effect of online instruction on learning outcomes, and this effect is driven by relatively math-intensive and quantitative courses. In this section, we further explore why female students learn substantially better in person than online, while men seem to learn equally well in two scenarios. We first examine whether men and women differ in their preference for online instruction (6.1). Then, we examine how online instruction differentially affects the learning experiences of men and women (6.2).

6.1 Gender differences in preferences

Self-reported preference: We first use a simple question in the endline survey to understand students' preference for the instruction mode. The question asks "*What kind of lectures would you personally prefer for the future? (Provided that the general Covid-19 situation allows this.)*" There are three answer options: (a) online lectures; (b) mixed/partial attendance; and (c) in-person lectures. Overall, we find that women are approximately 8 percentage points less likely than men (13.4% versus 21.1%) to choose online lectures as

their preferred mode—meaning that women are more likely to prefer "mixed attendance" or "in-person lectures." This gender gap is statistically significant at the 1% level (see Appendix Figure A.2).

Figure 4. Exposure to In-Person Instruction and Self-Reported Preference for Online Lectures



Notes: The figure how men's and women's likelihood of preferring online lectures varies with the average proportion of in-person lectures assigned in the Mathematics and Microeconomics courses from week 1 to week 3. The error bars indicate 95% confidence intervals.

We further examine how exposure to online versus in-person instruction affects students' self-stated preference (measured at the student level). Following the analysis in Section 5.5, we focus on the Microeconomics and Mathematics courses, and for ease of interpretation, we test how the proportion of in-person lectures affects the likelihood of reporting a preference for online lectures. Figure 4 shows that when the proportion of in-person lectures is relatively low, men and women are similarly likely to prefer online instruction (approximately 15%). However, as the proportion of in-person lectures increases in the two quantitative courses, women become less likely to prefer online instruction, while men become more likely to prefer online instruction. Appendix Table B.6 shows consistent estimation results using

linear probability models.[16] These results suggest that when exposed to more in-person lectures in the math-intensive courses, women (men) develop a stronger preference (distaste) for in-person rather than online instruction.

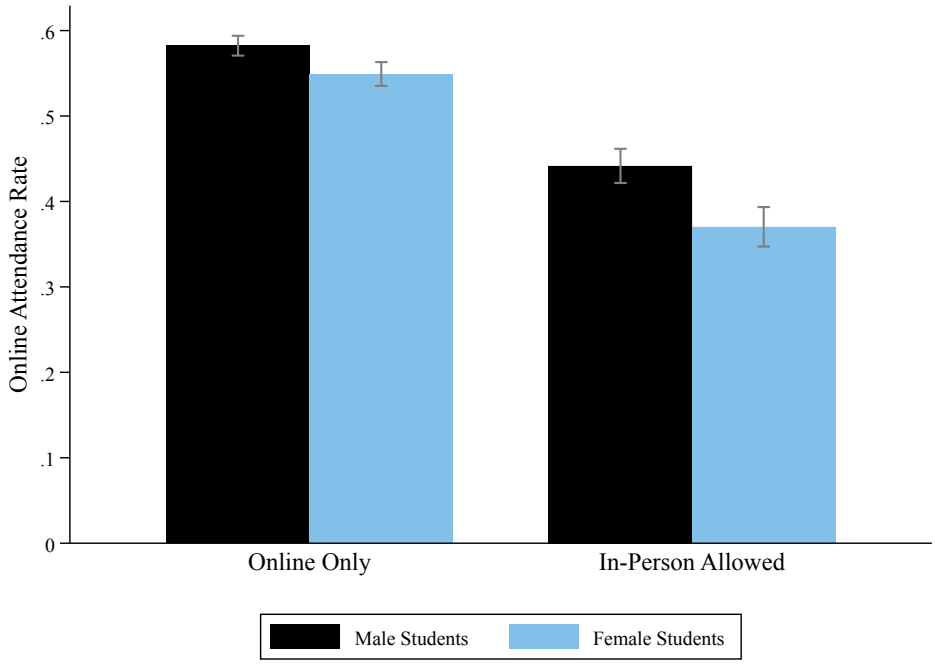
Revealed preference: To provide further evidence on the gender difference in preference, we analyze students' lecture attendance behavior as a proxy for revealed preference. As described in Section 3, we obtained records of students' online attendance for the Microeconomics course. We first use the data to examine how students online attendance varies with the assigned teaching mode. Figure 5 shows the attendance rate by gender in two conditions: when a lecture is assigned to be online for a student ("Online Only"); and when in-person attendance is allowed ("In-Person Allowed"). We find that in both conditions, male students are more likely than female students to attend online lectures. However, this gender gap is much larger when in-person attendance is allowed (7 percentage points) compared to when only online attendance is allowed (3 percentage points). This 4 percentage points difference in the gender gap suggests that women are more likely to attend lectures in person (instead of online) when in-person attendance is allowed, further implying that they have a stronger preference for in-person instruction.[17]

Our results above show that exposure to in-person versus online instruction affects students' self-reported preference for online lectures. In the same vein, we can test whether exposure to different teaching modes early in the semester influences students' lecture attendance later in the semester. Figure A.3 in the Appendix shows that women exposed to more in-person lectures in weeks 1 to 3 become less likely to attend lectures online in weeks 4 to 7, and the pattern is the opposite for men. Appendix Table B.7, Panel B, presents regression results confirming these patterns: As the proportion of in-person lectures in weeks 1 to 3 increases by 10 percentage points, women's online attendance rate in weeks 4–7 decreases by 3 percentage points, and the gender gap in the effect is statistically significant at the 1% level. Moreover, the results are similar when we focus on online attendance in weeks 5–7 or in weeks 6–7.

[16] Appendix Table B.6, Columns (1)–(2), show that an increasing proportion of in-person lectures in the Mathematics and Microeconomics significantly lowers women's tendency to prefer online instruction, but its impact on men's preference is statistically significantly different. Columns (3) and (4) show the estimated effect separately by gender: A 10 percentage points increase in the in-person proportion leads to a 6 percentage points decrease in women's likelihood of preferring online instruction and directionally raises men's preference for online instruction.

[17] Appendix Table B.7, Panel A, shows the regression results that confirm the graphical pattern. When in-person attendance is allowed for a lecture (rather than when only online attendance is allowed), women are 18 percentage points less likely to attend a lecture online. For men, the difference in online attendance by the assigned attendance mode is smaller by about 4 percentage points. The gender gap is statistically significant at the 1% level when controlling for student fixed effects.

Figure 5. Online Attendance Rate by Gender and Assigned Teaching Mode



Notes: The figures shows the fraction of male and female students attending online Zoom lectures in the Microeconomics course, depending on whether in-person attendance is allowed for a lecture. The sample includes 15,890 student-lecture-level observations across 7 weeks. Error bars indicate 95% confidence intervals. The differences between male and female students in both panels are statistically significant at the 1% level.

Collectively, our results in this section provide consistent evidence that female students hold a stronger preference for in-person instruction than male students. Moreover, the exposure to more in-person lectures (and fewer online lectures) appears to strengthen women's preference for in-person instruction.

6.2 Learning experiences

Although the gender difference in preference helps explain why online instruction differently affects the learning outcomes of women and men, we still do not fully understand the source of the gender-specific preference. For example, what aspects of in-person instruction do women like and men dislike? To provide suggestive evidence on this, we examine students' learning experiences reported in the endline survey how these experiences vary with the exposure to online versus in-person lectures. Overall, 53% of students in our analysis sample completed the survey, and the proportion of online lectures does not significantly affect the response rate of all students, women, or men in our sample (see Appendix Table B.8).

The endline survey measures four broad aspects of learning experiences in different courses, explained in detail below.

Extensive-margin attendance: We first ask students whether they attended any lectures of each enrolled course during the semester. Overall, 79% of students in the sample report that they attended at least one lecture of all the courses; 10% of students did not attend any lectures of any course; and the other 11% attended at least one lecture of some of the courses.

Overall course satisfaction: We use two questions to measure students' satisfaction with different courses: "*How much did you like [course name]*?" and "*Please evaluate the lectures of the following professors.*" Students answer both questions on a Likert scale from 1 (very poor) to 10 (very good). We standardize these two answers and create an inverse covariance weighted (ICW) index for overall course satisfaction, following the method of Anderson (2008). We further standardize this index to have a mean of 0 and a SD of 1.[18]

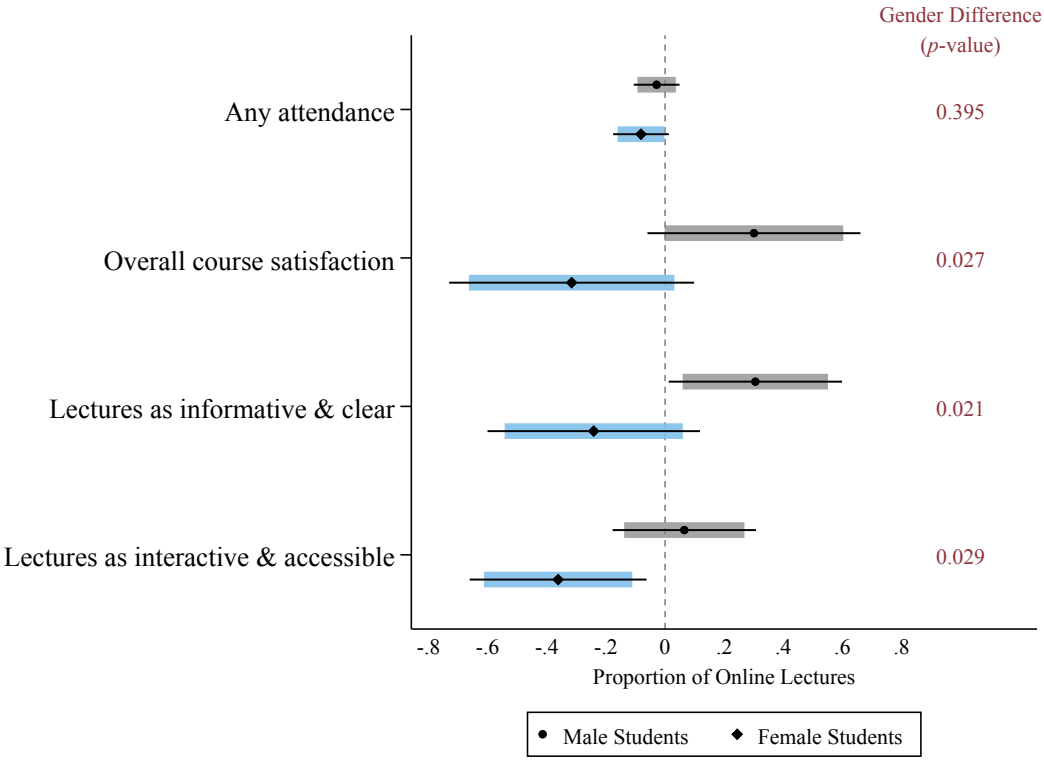
Lectures as informative and clear: An important aspect of lectures that can affect students' learning efficacy is whether they are informative and clear enough. To measure this, we ask students to report their agreement with two statements: "*The lectures helped me to better understand the course content*;" "*The lectures were clearly structured and easy to follow.*" The answer scale ranges from 1 (strongly disagree) to 10 (strongly agree). We combine the two answers into one ICW index to capture students' evaluation of lectures along this dimension.

Lectures as interactive and accessible: Another feature of lectures that may be crucial for learning is whether they are engaging enough and whether students can readily get support from the teacher and peers. We measure this feature using students' agreement with the following statements: "*The professor regularly encouraged students to actively participate in the lecture*;" "*The professor has been responsive to student questions;*" and "*Regarding the course, it was easy to contact other students when necessary*" all on a scale of 1 (strongly disagree) to 10 (strongly agree). Similarly, we create an ICW index to capture students' evaluation of lectures as interactive and accessible.

Based on these measures, we separately examine how exposure to online instruction affects the learning experiences of women and men across dimensions. The first two estimates

[18] We only ask students to report their course satisfaction and evaluation of lectures if they have attended at least one lecture of a course.

Figure 6. The Impact of Online Instruction on Learning Experiences



Notes: The figure shows the estimated effects of the proportion of online lectures on the following four outcomes: (1) an indicator for whether attending any lectures of a course; (2) a standardized index for overall satisfaction with a course: how much students like a course, and how they evaluate lectures overall; (3) a standardized index capturing students' evaluation of the lectures as informative and clear; and (4) a standardized index capturing students' evaluation of lectures as interactive and accessible. Outcome 3 is measured with students' agreement with two statements: "*The lectures helped me to better understand the course content*" and "*The lectures were clearly structured and easy to follow.*" Outcome 4 is measured with agreement with three statements: "*The professor regularly encouraged students to actively participate in the lecture*;" "*The professor has been responsive to student questions;*" and "*Regarding the course, it was easy to contact other students when necessary.*" For each outcome, we use a model including two interaction terms $\%Online \times Female$ and $\%Online \times Male$ to estimate the impact of online instruction on men and women. We then test the difference between the two interaction terms and report the p-value. Each regression controls for student fixed effects and course fixed effects and cluster standard errors at the student level. Error bars indicate 90% and 95% confidence intervals.

in Figure 6 show that an increasing proportion of online lectures lowers the extensive-margin course attendance of both men and women, but only the effect on women is statistically significant. Conditional on attending any lectures of a course, early exposure to online instruction systematically lowers women's satisfaction with a course and their evaluations of lectures in terms of their clarity and engagement. By contrast, online instruction directionally raises men's course satisfaction and evaluations. The gender differences in the effects of online instruction are statistically significant at the 5% level across all dimensions (see the last three pairs of estimates in Figure 6).

Taken together, the results in this section show that compared to men, women are less satisfied with online lectures, possibly because they consider online lectures as less informative and less interactive. As documented in prior work, the "gender digital divide" implies that women may not be comfortable with using digital tools for learning purposes, compared to men. Women may also have a stronger demand for social interactions in the learning process. As a result, the lack of engagement and peer support in online learning environments may also hamper their learning outcomes.

7 Conclusion

Although online instruction is increasingly used in schools and universities, we have limited knowledge about the equity implications of introducing online instruction. Given that female students tend to engage less with technological tools and benefit more from interactive learning environments, they may get disproportionally disadvantaged when educational institutions introduce online instruction. We provide the first rigorous experimental evidence for the gender gap in the effect of online instruction.

To pin down the gender gap, we conduct a field experiment in which a cohort of over 1,300 students at an international business school are randomly assigned to varying compositions of online versus in-person lectures across courses. Using these within-student, cross-course variations, we find that women exposed to more online lectures obtain significantly lower exam score compared to women exposed to fewer online lectures. By contrast, exposure to online versus in-person instruction does not significantly affect men's exam performance. The gender gap in the effect is precisely estimated and robust to multiple testing corrections. When examining heterogeneity across courses, we find that the negative effect of online instruction is driven by math-intensive courses; exposure to more online lectures in these courses also decreases women's longer-term educational attainment.

We further use rich survey and lecture attendance data to explore possible mechanisms underlying the gender disparities in the effect of online instruction. We find suggestive evidence that women have a lower preference than men for online lectures—for both preference self-reported by students and preference revealed through their attendance behaviors. Exposure to online lectures also differentially affects the learning experiences of women and men: compared to men, women exposed to more online lectures evaluate the course as less informative and less interactive and report lower course satisfaction.

Our findings are relevant for education policymakers offering online instruction or designing hybrid instruction. Instead of only evaluating the overall benefits versus costs of introducing online teaching, policymakers should be especially mindful of how online instruction

affects minority or disadvantaged groups—as highlighted in Bacher-Hicks, Goodman and Mulhern (2021) and Jack and Oster (2023). Our sample composes of students in business, economics, and informatics fields, where women are underrepresented and consistently perform worse than men. In such settings, shifting toward online instruction may enlarge the existing gender gap in educational attainment.

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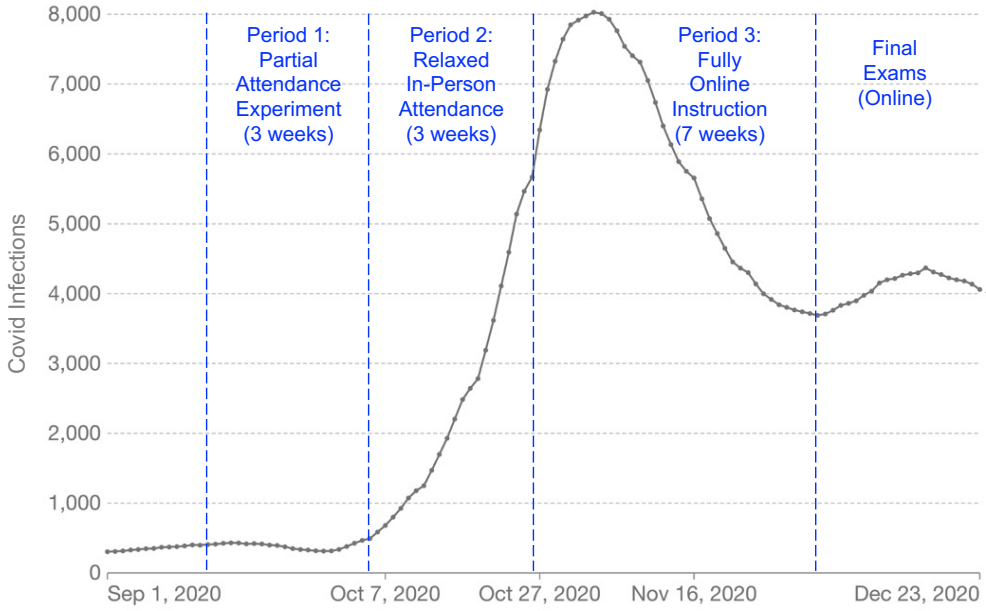
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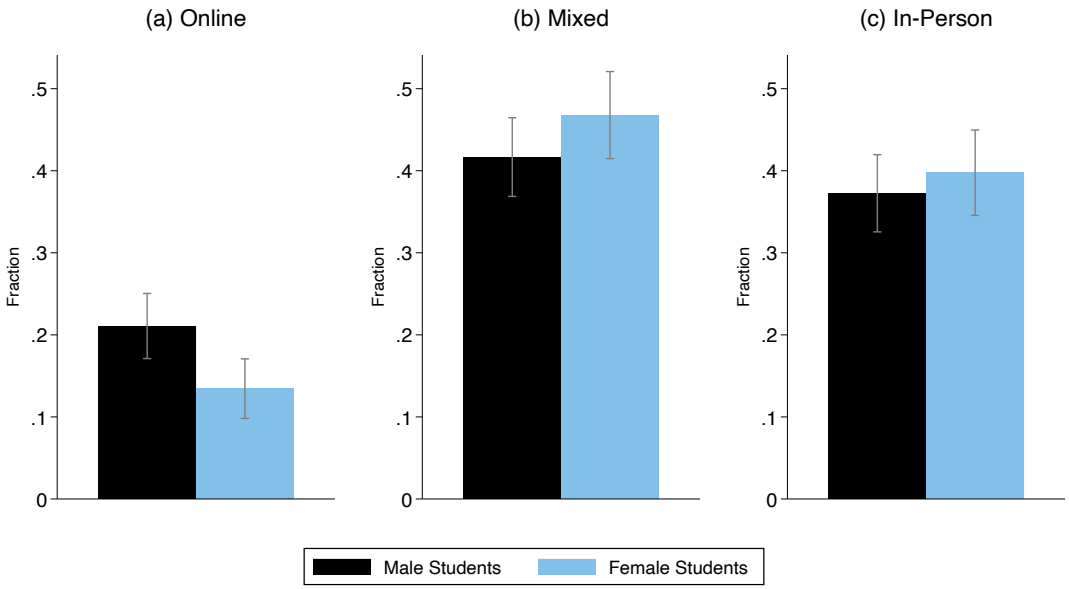
A Additional Figures

Figure A.1. A Timeline of the Experiment and the Covid Situation



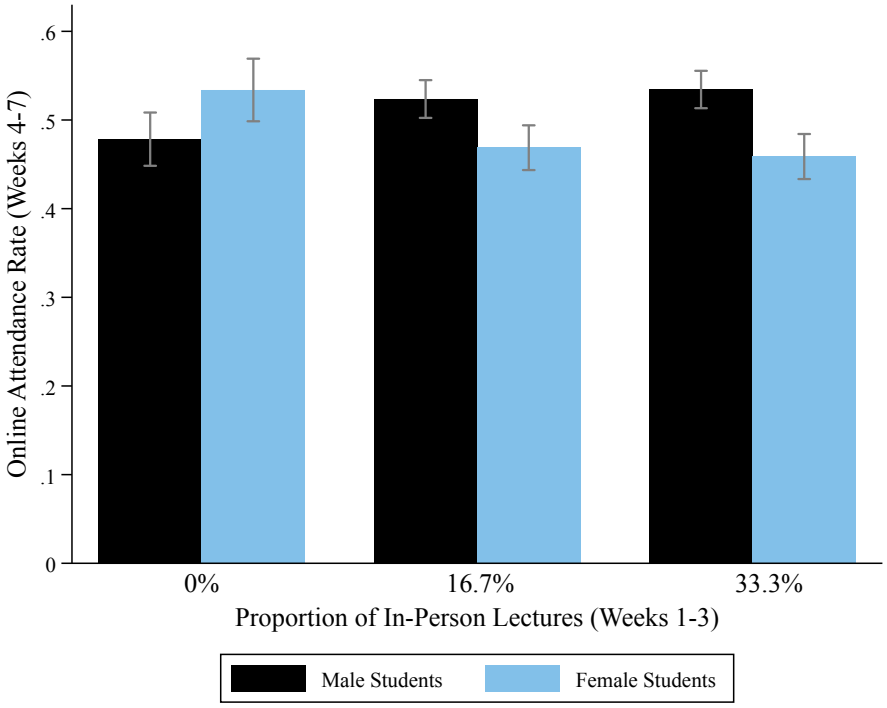
Notes: The figure shows a timeline of the experiment during the fall semester of the 2020/21 academic year. The gray curve in the background shows the number of Covid infections in the country. The blue texts indicate the three periods of the semester. (1) The first three weeks were the period when we conducted the partial attendance experiment—20% of students were permitted to show up on campus at any given time. (2) During the next three weeks, the university relaxed in-person attendance restrictions. (3) During the last seven weeks of the semester, all instruction was moved online due to the surge in Covid infections. All final exam were administered online.

Figure A.2. Preference for Different Teaching Modes by Gender



Notes: The figure shows the fraction of male and female students who prefer each type of instruction mode, with 95% confidence intervals. The question is: "*What kind of lectures would you personally prefer for the future? (Provided that the general Covid-19 situation allows this.)*" The three options are online lectures, mixed/partial attendance, and in-person lectures. The gender difference in Panel (a) is statistically significant (p-value = 0.006). In Panels (b) and (c), the gender difference is not significant.

Figure A.3. Early In-Person Exposure and Later Online Attendance



Notes: The figure shows how the online attendance rate of men and women in weeks 4 to 7 varies with the proportion of in-person lectures assigned in weeks 1 to 3. The sample includes 9,080 student-lecture-level observations. Error bars indicate 95% confidence intervals. For each level of assigned in-person lectures, the gender gap in attendance rate is statistically significant at the 5% or 1% level.

B Additional Tables

Table B.1. Descriptive Statistics by Student Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Female Students			Male Students			Gender Difference
	N	Mean	SD	N	Mean	SD	p-value
Panel A: Student Characteristics							
Age	548	20.95	2.400	796	21.59	2.619	0.005
International Student	548	0.162	0.369	796	0.153	0.360	0.651
Commute Time to University (Minutes)	548	37.96	38.04	796	38.15	35.09	0.928
Business/Economics/Finance Majors	548	0.518	0.500	796	0.606	0.489	0.001
Informatics Majors	548	0.097	0.296	796	0.245	0.430	<0.001
Other Majors	548	0.385	0.487	796	0.149	0.357	<0.001
High School Grade	388	4.714	0.510	504	4.623	0.510	0.008
High School Self-Study Intensity	387	0.767	0.183	493	0.772	0.215	0.715
Group Study Preference	388	4.279	0.970	504	4.237	0.899	0.506
Conscientiousness	388	4.926	0.988	504	4.696	0.917	<0.001
Extraversion	388	4.855	1.288	504	4.663	1.203	0.023
Panel B: Exam Performance							
Total Course-Level Score	1,502	32.99	18.89	2,268	35.00	18.84	0.001
Question-Level Points	47,667	1.037	1.369	69,832	1.134	1.372	<0.001

Notes: The table shows the summary statistics of student-level characteristics and exam performance outcomes separately for the sample of women (in Columns 1–3) and men (in Columns 4–6). Column (7) shows the p-values derived from tests of gender difference. See Table 1 for summary statistics for the whole sample and details of student characteristics.

Table B.2. Balance Tests by Gender

(1)	(2)	(3)
	Effect of Online Proportion	
Dependent Variable	Women	Men
Age	0.290	-0.501***
	(0.201)	(0.179)
International Student	0.007	0.000
	(0.033)	(0.025)
Business/Economics/Finance Majors	0.069	-0.036
	(0.053)	(0.037)
Informatics Majors	-0.006	0.013
	(0.020)	(0.029)
Other Majors	-0.063	0.024
	(0.056)	(0.033)
Commute Time to University (Minutes)	2.540	-0.712
	(3.120)	(1.980)
High School Grade	-0.023	-0.019
	(0.047)	(0.035)
High School Self-Study Intensity	-0.012	0.001
	(0.016)	(0.015)
Group Study Preference	-0.100	-0.008
	(0.090)	(0.066)
Conscientiousness	-0.046	0.017
	(0.098)	(0.064)
Extraversion	-0.043	-0.081
	(0.124)	(0.084)

Notes: The table shows the estimated effects of the proportion of online lectures (*Online Proportion*) on different baseline characteristics, separately for women and men in our sample. Each point estimate is derived from one OLS regression, in which we control for course fixed effects and cluster standard errors at the student level. We report the estimated coefficients and standard errors (in parentheses) of each baseline characteristic. $^{*}p$ <.1, $^{**}p$ <.05, $^{***}p$ <.01.

Table B.3. The Impact of Online Instruction on Final Grade and Course Pass

	(1)	(2)	(3)	(4)
	Std. Final Grade		Course Passing	
	Women	Men	Women	Men
% Online Lectures	-0.473***	0.085	-0.204***	0.022
	(0.115)	(0.092)	(0.069)	(0.051)
Observations	1,401	2,087	1,401	2,087
R-squared	0.725	0.754	0.548	0.570

Notes: The table shows the estimated impact of online instruction on final course grade (standardized across the whole sample) and the likelihood of passing a course (i.e., at least obtaining a grade of 4). Each column represents one regression. Results are estimated with OLS regressions in Columns (1)–(2) and linear probability models in Columns (3)–(4). All regressions control for student fixed effects and course fixed effects. Standard errors in parentheses are clustered at the student level. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Table B.4. Heterogeneity of the Impact by Various Student Attributes with Multiple Testing Corrections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: Standardized Exam Score								
% Online	-0.379***	0.082	-0.032	-0.118	-0.108	-0.067	-0.198**	-0.099	-0.151*
	(0.085)	(0.133)	(0.116)	(0.076)	(0.087)	(0.084)	(0.081)	(0.084)	(0.087)
	[0.001]	[0.953]	[0.980]	[0.271]	[0.542]	[0.890]	[0.017]	[0.637]	[0.145]
% Online × Male	0.409***								
	(0.108)								
	[0.001]								
% Online × International Student		0.256*							
		(0.145)							
		[0.140]							
% Online × Bus./Fin./Econ. Majors			-0.132						
			(0.130)						
			[0.759]						
% Online × Higher Commute Time				-0.024					
				(0.106)					
				[0.980]					
% Online × Higher High School Grade					-0.036				
					(0.110)				
					[0.980]				
% Online × Higher Conscientiousness						-0.107			
						(0.108)			
						[0.764]			
% Online × Higher Extraversion							0.112		
							(0.107)		
							[0.759]		
% Online × Higher Self-Study								-0.050	
								(0.109)	
								[0.977]	
% Online × Higher Group Study Preference									0.034
									(0.110)
									[0.980]
Observations	3,488	3,488	3,488	3,488	3,488	3,488	3,488	3,488	3,488
R-squared	0.839	0.838	0.838	0.838	0.838	0.838	0.838	0.838	0.838

Notes: The table shows the effects of the proportion of online lectures in weeks 1–3 (*% Online*) and its interaction effects with different student attributes (see Table 1 for details of these characteristics). "*Bus./Fin./Econ. Majors*" is a binary indicator for business, finance, or economics majors. "Higher" means that the value of a characteristic is above the median level. Each column represents one OLS regression in which we control for both student fixed effects and course fixed effects. Standard errors are clustered at the student level and in parentheses. $*p < .1$, $**p < .05$, $***p < .01$. We also present Romano-Wolf corrected p-values in brackets based on 1,000 resampling of student clusters (each student may have multiple course observations) within the strata of assigned attendance groups.

Table B.5. The Long-Term Impact of Online Instruction by Course

	(1)	(2)	(3)	(4)
Dependent Variable: Standardized Overall Index				
% Online Lectures in Mathematics	-0.801**			
	(0.401)			
% Online Lectures in Mathematics × Male	1.042**			
	(0.476)			
% Online Lectures in Microeconomics		0.037		
		(0.434)		
% Online Lectures in Microeconomics × Male		0.015		
		(0.552)		
% Online Lectures in Financial Accounting			0.288	
			(0.368)	
% Online Lectures in Financial Accounting × Male			0.048	
			(0.464)	
% Online Lectures in Business Administration				0.337
				(0.347)
% Online Lectures in Business Administration × Male				-0.777*
				(0.441)
Observations	742	820	680	798
R-squared	0.086	0.070	0.068	0.082

Notes: The table shows the estimated effects of online instruction in different courses on students' long-term educational attainment—a standardized index capturing the share of credits earned in the 2020/21 academic year and the chance of remaining enrolled in the fall or spring semester of the 2021/22 academic year. Each column represents one OLS regression, controlling for student gender, age nationality, major category, and commute time. The estimation sample includes the first-year students in our sample who are enrolled in each course in the fall semester of 2020; the sample size thus varies across columns. Robust standard errors are in parentheses. *p <.1, **p <.05, ***p <.01.

Table B.6. In-Person Exposure in Quantitative Courses and Preference for Online Lectures

	(1)	(2)	(3)	(4)
	Dependent Variable: Prefer Online Lectures			
	All	All	Women	Men
% In-Person in Micro/Math	-0.739***	-0.537**	-0.562**	0.409
	(0.254)	(0.255)	(0.256)	(0.309)
% In-Person in Micro/Math × Male	1.132***	0.934**		
	(0.402)	(0.399)		
Male	-0.166*	-0.145*		
	(0.089)	(0.088)		
Observations	451	451	189	262
R-squared	0.022	0.076	0.100	0.067
Student controls	No	Yes	Yes	Yes

Notes: The table shows the effects of in-person instruction in two math-intensive courses on the likelihood of preferring online lectures, estimated with linear probability models. The dependent variable is a binary indicator for a student reporting "online lectures" as the preferred teaching mode. The key variable of interest is the average proportion of in-person lectures assigned in the Mathematics and Microeconomics courses (ranging from 8.6% to 25%). The student controls in Columns (2)–(4) include nationality, age, commute time, and major. Robust standard errors are in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Table B.7. Online Lecture Attendance by Assigned Attendance Mode and Early Exposure to In-Person Instruction

	(1)	(2)	(3)	(4)	(5)
	Panel A: Online Attendance in ... Weeks 1–7		Panel B: Online Attendance in ...		
			Weeks 4–7	Weeks 5–7	Weeks 6–7
In-Person Allowed	-0.175***	-0.180***	-0.108***	-0.099***	-0.050**
	(0.014)	(0.012)	(0.012)	(0.015)	(0.023)
In-Person Allowed × Male	0.039**	0.040***			
	(0.018)	(0.015)			
% In-Person Lectures (Weeks 1-3)			-0.226***	-0.264***	-0.357***
			(0.064)	(0.074)	(0.094)
% In-Person Lectures (Weeks 1-3) × Male			0.282***	0.320***	0.389***
			(0.084)	(0.096)	(0.118)
Male	0.019**		-0.012	-0.023	-0.045
	(0.009)		(0.020)	(0.023)	(0.028)
Observations	15,890	15,890	9,080	6,810	4,540
R-squared	0.051	0.508	0.073	0.076	0.081
Lecture Fixed Effects	Yes	Yes	Yes	Yes	Yes
Student Fixed Effects	No	Yes	No	No	No

Notes: Panel A shows how the online attendance for a lecture depends on the assigned attendance mode of this lecture for a student (either online only or in-person allowed). Panel B estimates how the proportion of in-person lectures assigned in weeks 1 to 3 affects the online attendance rate in later weeks of the semester. The dependent variable in all columns is a binary indicator for attending a lecture online. The analysis uses student-by-lecture observations for the Microeconomics course. All regressions control for lecture fixed effects. The model in Column (2) controls for student fixed effects, and other models control for students' major, nationality, age, and commute time. Standard errors in parentheses are clustered at the student-by-lecture level. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Table B.8. Exposure to Online Instruction and Endline Survey Response

	(1)	(2)	(3)	(4)
	Dependent Variable: Endline Survey Response			
Panel A: All Students				
% Online Lectures in Financial Accounting	0.014			
	(0.077)			
% Online Lectures in Business Administration		-0.095		
		(0.097)		
% Online Lectures in Mathematics			-0.056	
			(0.065)	
% Online Lectures in Microeconomics				-0.086
				(0.080)
Female	0.148***	0.114***	0.098***	0.106***
	(0.037)	(0.034)	(0.034)	(0.032)
Observations	820	999	915	1,036
R-squared	0.022	0.015	0.018	0.024
Panel B: Female Students				
% Online Lectures in Financial Accounting	-0.011			
	(0.108)			
% Online Lectures in Business Administration		-0.216		
		(0.152)		
% Online Lectures in Mathematics			-0.169	
			(0.104)	
% Online Lectures in Microeconomics				-0.165
				(0.108)
Observations	336	410	328	428
R-squared	0.002	0.014	0.021	0.026
Panel C: Male Students				
% Online Lectures in Financial Accounting	0.048			
	(0.115)			
% Online Lectures in Business Administration		-0.017		
		(0.127)		
% Online Lectures in Mathematics			0.035	
			(0.084)	
% Online Lectures in Microeconomics				-0.026
				(0.116)
Observations	484	589	587	608
R-squared	0.022	0.014	0.019	0.019

Notes: The table presents the estimated impact of the proportion of online lectures in each course (if enrolled in the course) on the response rate for the endline survey. The dependent variable is a binary indicator for completing the endline survey. Panel A includes all students; Panel B/C includes female/male students in our sample. Each column in each panel represents one linear probability model that controls for major, nationality, age, and commute time. Robust standard errors are in parenthesis. $^{*}p$ <.1, $^{**}p$ <.05, $^{***}p$ <.01.