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Do Students Perform Better in Online Delivery of Education? Evidence from Bangladesh[1]

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Abstract

The COVID-19 pandemic has forced educational institutions in Bangladesh to adopt online technology for higher education in just a couple of months that, otherwise, would have taken years. This change creates a unique opportunity to examine student performance in online education. In this study, in addition to examining the effect of online education on student performance, we investigate if there is a systematic difference in grading. We use transcript-level academic records of Business and Economics students from one of the leading private universities in Bangladesh for pre-pandemic and pandemic periods. We use two-way fixed effects regression models to eliminate entity- and time-specific fixed effects that may bias our estimates. Student level grade points in online format are higher by about 0.208 (on a scale of 0 to 4). This increase in grade points in online format is driven by the poorly performing student. Course level estimates show that the average grade points increase by about 0.086 which comes from a narrower distribution. The reduction in variance in grade points may be the result of online collaboration among students, more lenient grading by the instructors due to the pandemic situation or because of using increased group activities for assessment. We also find the effect of online format on course level average grade points (AGP) decreases and the coefficient of variation (CV) increases as instructors gain experience indicating some learning effects.

JEL Classification: A20, I21, I23

Keywords: COVID-19; education; online education; student performance; cheating; Bangladesh.

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1 Introduction

The COVID-19 pandemic has changed the education system in Bangladesh beyond recognition. It has forced the educational institutions in the country to adopt online technology for higher education in just a couple of months that, otherwise, would have taken years. In contrast to the western world, there were no online higher education programs in the country prior to the pandemic. To put it in context, for example, about 1 in 3 students take at least one online course at the higher education level in the US (Allen and Seaman, 2013). During this pandemic, most private universities and a few public universities in Bangladesh have adopted online technology to continue academic activities. Though online education is new in the country, this cost-saving mode of education is likely to stay in the post-pandemic period. So it is crucial to understand how online education affects student performance compared to traditional face-to-face instruction.

Existing literature on online education is mostly based on western universities and the findings are inconclusive. Some studies show that student achievement in online classes is almost the same as in face-to-face instruction (Bowen et al. 2014; Means et al., 2009; Bell and Federman, 2013). For example, using a randomized experiment, Bowen et al. (2014) measure the effect of a sophisticated hybrid format compared to a traditional format on student performance for an introductory statistics course in multiple US universities. Their findings suggest that learning outcomes are essentially the same. The hybrid format does not affect students in terms of pass rates, final exam scores, and performance on a standardized assessment of statistical literacy.

On the other hand, some studies show that online education hurts student performance compared to face-to-face instruction. Alpert, Couch and Harmon (2016) conduct a randomized experiment in a large public university in the US for an introductory microeconomics course to assess the impact of instruction formats. They find that students in the purely online form perform poorly compared to face-to-face and blended format (about 5 to 10 points lower in a cumulative final exam). Bettinger et al. (2017), using an instrumental variable method, show that in a large for-profit university in the US, students enrolled in online classes earn lower grades and are less likely to remain enrolled at the university. Figlio, Rush and Yin (2013), in a randomized experiment of teaching introductory microeconomics at a research university in the US, find a modest positive effect of face-to-face instructions and the effects are stronger for low achieving students, males, and some minority students. Brown and Liedholm (2002) also find a negative impact of online education on student achievement in their study on teaching principles of microeconomics at Michigan State University.

Performance in online education may differ from face-to-face depending on how the tests are conducted. Unproctored online tests may encourage students to adopt unfair practices in exams.[5] Some studies explore if student performance differs in proctored and unproctored online exams. Harmon and Lambrinos (2008), using data from two online courses, find evidence of cheating in unproctored online exams while Hollister and Berenson (2009), on the other hand, do not find any evidence of cheating in unproctored online exams. Watson and Sottile (2010), using self-reported data on cheating in examinations, show that 32.1% of the students in face-to-face courses and 32.7% in online courses admitted to cheating. The difference is negligible and statistically insignificant, which they interpret as the absence of more cheating in online tests. Using a game-theoretic approach, Bilen and Matros (2021) show that cheating should be expected in online examinations. They provide evidence of cheating in online examinations using data from an intermediate-level course at a large private university in the US when academic activities moved online in the middle of the Spring 2020 semester. They use time-stamped student access log provided in Blackboard and find that two students cheated in online examinations. However, a comparison of the student performance in the course in spring 2020 with the same over the past ten years suggests that probably more than two students cheated in online examinations. Fask, Englander and Wang (2014) randomly assigned the students to face-to-face or online format for the final examination and provide suggestive evidence of cheating in the online examination. Diedenhofen and Musch (2017) develop PageFocus, a JavaScript to detect if the test takers switch to different pages while taking the test. They find that test takers are more likely to cheat when performance-based incentives are offered. They also find that generating a popup message asking not to cheat when test-takers change the window or browser tab can reduce cheating. Karim, Kaminsy and Behrend (2014) conduct an experiment to understand test takers' performance in online proctored and unproctored environments. They used Amazon's MTruck platform to recruit test takers and administered two tests – one searchable online and the other nonsearchable. The authors find that webcam monitoring reduces performance for searchable tests but not for nonsearchable tests, indicating that unproctored online test takers are likely to cheat. They also find that webcam monitoring increased pressure as well as concerns over privacy. So most of the studies indicate students are more likely to adopt unfair practices in unproctored examinations except for the self-reported study.

Given the wide variety of online education, it is not unusual that some studies show adverse effects while others find a null impact of online education. McPherson and Bacow (2015) identify several versions of online instructions – (1) asynchronous mode, (2) partially asynchronous mode, (3) blend/hybrid mode, and (4) flipped classroom. The format of online instructions followed by the university in this study does not

[5] Needless to say, students may also adopt unfair means in proctored exams.

conform to any of these versions. Rather, we can add another version of online education - synchronous mode where teachers meet students online during scheduled class time, just like in face-to-face classes. Apart from the different versions of online education, there are also differences in estimation techniques used in different studies and are likely to contribute to the mixed findings.

The sudden transition from face-to-face to online education due to the pandemic creates a unique opportunity to examine the effect of online education on student performance in Bangladesh. Some of the educationists in the country are also concerned about whether students are adopting unfair practices while taking their tests online. So the objectives of this paper are to (1) investigate the effect of online education on student performance and (2) examine if there is any evidence of a difference in grading. This difference can originate from multiple factors such as teachers and students coping with the new technology, students adopting unfair practices while taking unproctored tests online. We employ three empirical models to address these issues. The first two models focus on students' grade change in online education. The third model addresses the case of a systematic difference in performance. Identifying the true effect of online format on student performance is difficult since some characteristics are not observable to the researchers that may determine student performance in online education. For example, students may differ from one another in terms of their tech-skill to cope with the new technology. Students may not have the necessary device to work well in online format. Or even the quality of internet connections may be different for different students. So we employ two-way fixed effects regression models to eliminate any time and entity specific factors from the models that may bias the effect of online education.

We use academic records of business and economics students from one of the leading private universities in Bangladesh. The analyses are conducted at two levels - student and course levels. Results from student level analysis show that the online format increases students' course grade points by about 0.208 points (on a scale of 0 to 4). We also find that students at the top of the performance distribution do not benefit from the online format at all. The increase in grades is mainly driven by students at the bottom of the distribution. The course level analysis shows that the average grade points is about 0.086 points higher in the online format which is not large enough to change the average grade. Using the coefficient of variation (CV) of course-level grade points, we also find that the higher grade points come from a narrower distribution in the online format. That is, both student and course level analysis provide evidence of grade inflation in the online format. Further examination shows that the effect of online format on course level CV decreases as instructors gain experience indicating some learning effects.

This paper contributes to the existing literature in three ways. First, since online education is new in Bangladesh, this paper would be the first to provide any evidence on how online education affects student performance.[6] Second, we use a large data set of administrative records of students' academic achievement instead of one or two course-based analysis, or self-reported data most widely used in the literature. Finally, we offer a means to test if there is any systematic difference in performance in unproctored online tests.

The remainder of the paper is organized as follows. Section 2 discusses the conceptual framework, while Section 3 lays out the empirical strategy of this study. Section 4 discusses the data and the summary statistics. Section 5 presents the results of the paper, followed by robustness checks in Section 6. Section 7 highlights the main findings and concludes the paper with some policy recommendations.

2 Conceptual Framework

At this early stage, online education in Bangladesh could face many challenges affecting students' academic achievement. These challenges could also make it difficult for educational institutions to deliver the best possible educational services. So it is crucial to understand how online education affects student performance in the country.

As pointed out earlier, the existing literature provides mixed evidence on the effect of online education vis-à-vis in-person education. Some studies show a negative effect of online education (Bettinger et al., 2017; Figlio, Rush and Yin, 2013), while others find a null effect (Bowen et al., 2014; Means et al., 2009; Bell and Federman 2013). However, these findings implicitly agree on one thing – online education does not have a positive effect on student performance compared to in-person classes. It is not surprising that results are diverse as the nature of online education varies widely from recorded video lessons with unproctored tests to "Interactive Learning Online" (ILO) as well as the differences in estimation techniques.

In order to estimate the effect of online education on student performance in Bangladesh, it is necessary to understand the potential challenges and the advantages of online education. Some of the challenges that may negatively affect student performance include relatively poor IT infrastructure[7], difficulty in coping

[6] Needless to say, given the overwhelming preponderance of the US based studies, this research would add value to the literature.
[7] According to Bangladesh Telecommunication Regulatory Commission's (BTRC) data, at the end of February 2021, only 9.522 million people in the country had access to broadband network (in a country of about 165 million people). Retrieved on April 21, 2021, from http://www.btrc.gov.bd/content/internet-subscribers-bangladesh-february-2021

with new delivery mechanisms (faced by both students and teachers), and not owning the necessary devices for online education. For example, some students use cell phones to participate in online classes instead of computers. Besides, the lack of peer-to-peer interactions among students that come with the in-person classes may also have an adverse effect on student performance. Additionally, success in online education also depends on self-discipline, the lack of which may negatively affect student performance (Banerjee and Duflo, 2014).

There are some advantages of online education as well. Online classes can eliminate travel costs almost entirely, which may require a significant amount of time, energy, and money in a country like Bangladesh. For example, a World Bank report in 2018 shows that Dhaka is one of the most congested cities in the world, and the average driving speed has dropped from 21 kilometers to 7 kilometers per hour in a decade. It is expected to go below average walking speed if the trend continues (Bird et al., 2018). So online classes help students save time, energy, and money that can be utilized for study purposes. Other factors that may positively affect grades are leniency in grading (during the pandemic period), grading format, and adoption of unfair practices.

Teachers might become lenient in grading during the pandemic considering the fact that everyone is going through a tough time. The assessment methods may also have a significant impact on performance. Since online teaching is a new technology for most teachers in the country, their assessment methods may differ from those used in face-to-face classes. For example, a teacher might assign more group activities, such as writing papers and making presentations in groups, and each member of the group will receive the same credit for the group work. Students can also cheat through collaboration among students (Facebook groups or other similar platforms) or by getting help from someone else during a test. Hence, the net effect is ambiguous. If the data show positive effects, this could result from a systematic difference in assessment methods in online unproctored tests and/or a combination of both. However, one might argue that the positive effects are driven by either a better student pool or the positive impact of saved travel time dominating negative factors. Taking appropriate measures to control for the student-specific effects may address this issue.

Student performance in online format may also depend on the subject matter. For example, the outcome in recalling information or computational testing skills could yield different results than testing conceptual grasp or problem-solving abilities (McPherson and Bacow, 2015). So, student performance in different types of courses, such as upper-level courses vs. other courses (non-upper level) can capture the heterogeneous effect of online education on student performance.

Identifying a positive, negative, or null effect of online education does not reveal much about grade distribution except that the distribution is shifting to the right or left. So we need a different approach to address this issue. If students adopt unfair means in tests, teachers become lenient and assign more group activities, then the grades in online classes will come from a narrower distribution. Suppose the grade points in face-to-face and online classes are GP^{f2f} and GP^{ol}, and the variances are V^{f2f} and V^{ol}, respectively. If online education has a positive effect, then $GP^{f2f} < GP^{ol}$. Additionally, if online format leads to a narrower distribution of the grade points, we will observe a smaller variance in online classes, $V^{f2f} > V^{ol}$, irrespective of the mean grade points of face-to-face and online classes. That is, the grades in online and face-to-face classes come from distributions that differ not just in mean but also in the spread of the distributions.

3 Empirical Strategy

To estimate the effect of online education on academic performance, we use two empirical models as shown in equations (1) and (2). The first model focuses on students' course grade points (GP) and the second model compares the course-wise average grade points (AGP). As pointed out earlier, better or poorer performance in online format may be driven by different assessment methods and/or cheating in unproctored online tests. The final model uses dispersions of course-wise grade points to explore if the second moments of the distributions are different. However, the data does not allow us to isolate the relative contribution of the grading style and cheating, meaning the differences in second moments could be because of the grading style alone, cheating alone or a combination of both. Equation (3) thus captures the full effect of online format on the variation of course grades.

The three models are as follows.

$$GP_{ics} = \alpha_1 + \alpha_2 \times online_{ics} + \delta X'_{ics} + S_i + I_i + C_c + T_s + e_{ics} \qquad (1)$$

where GP_{ics} is the grade points of student i in course c in semester s, online equals 1 if classes are conducted online and 0 otherwise, S_i represents student fixed effects, T_s represents time fixed effects, and X' is a vector of other covariates and e is the error term.

$$AGP_{cst} = \beta_1 + \beta_2 \times online_{cst} + \gamma Z'_{cst} + I_t + T_s + u_{cst} \qquad (2)$$

where AGP_{cst} is the average grade point of course c taught by instructor t in semester s, online equals 1 if classes are conducted online and 0 otherwise, I_t and T_s are the course-instructor and time fixed effects respectively, Z' is the vector of other covariates and u is the error term.

$$CV_{cst} = \theta_1 + \theta_2 \times online_{cst} + \phi Z'_{cst} + I_t + T_s + v_{cst} \quad (3)$$

where CV_{sct} represents the coefficient of variation of the grade points in course c taught by instructor t in semester s, I_t and T_s are the course-instructor and time fixed effects, respectively, Z' is the vector of other covariates and v is the error term.

Our interest lies in the values of α_2, β_2, and θ_2. The values of α_2 and β_2 represent the impact of online education on student performance which can be positive, negative or zero depending on how online education affects their academic performance. The value of θ_2 indicates if online format leads to a systematic difference in grading and/or cheating. The shift to online format was completely exogeneous, purely because of the pandemic. So, α_2, β_2, and θ_2 are supposed to be the causal effects of online education on student performance. However, as mentioned in the previous section, some factors might differently affect student performance in online and face-to-face formats and are not directly observable. Failing to control for those factors would lead to a biased estimate of the coefficient of the online variable. For example, a student who is more comfortable in using a computer is likely to do better in online format. Since we do not observe their tech-ability, the coefficients of the online variable may capture that effect leading to an upward bias of the online effect. Some students use smartphones instead of computers to participate in online classes and tests. As one would expect, students using smartphones instead of computers may perform poorly. To eliminate the unobserved heterogeneity among students, courses, and course instructors, we include student, course and instructor fixed effects wherever appropriate in (1), (2) and (3). Additionally, we also include time fixed effects in all models to capture the changing online environment.

One limitation of this study is the lack of a contemporary control group. That is, there are no variations in the type of courses taken in a semester (only in-person before the pandemic and only online since the pandemic). Despite this limitation, the empirical setting has a few advantages. First, the variation in course-taking behavior here is induced purely exogenously by the COVID-19 pandemic. Some of the earlier studies used an instrumental variable approach (Bettinger et al., 2017) to estimate the local average treatment effect. However, in this study, all students and teachers are affected due to the pandemic leading to a global treatment effect. Another benefit of the studies is the design. We can examine not only the impact on course-wise student performance but also the average grade points in a course. Another contribution of this paper is that we also examine if there is any evidence of a systematic difference in grading and/or adoption of unfair practices by students in online courses.

4 Data

We use administrative student records from one of the leading private universities in Bangladesh (henceforth the university) to examine the impact of online education on student performance. Before discussing the data, it is necessary to understand how the university operates. The university has three full-fledged semesters with roughly four months each. Generally, the semesters cover the following months – spring from January to April, summer from May to August, and fall from August to December. However, this schedule has changed a little due to university closure at the beginning of the pandemic. The university tries to follow a common assessment technique – two midterms, final exams, and other assessments methods such as quizzes, homework assignments, etc. The midterms and the final examinations generally account for most of the course grades. The university does not have a readily available database of student performance in different assessment modes, but it maintains a database of course-wise student grades. So, we have records of grades[8] for both pre-pandemic and pandemic periods in addition to some basic demographic characteristics of undergraduate students and teachers of the Faculty of Business Administration and Economics from fall 2016 to spring 2021. The university has been conducting academic activities online since mid-spring 2020.

The analyses in this paper are conducted at two levels – student level and course-instructor level. The sample includes a panel of 3,200 students for 14 semesters with 76,082 observations. The sample includes only those students who enrolled in at least one online semester and one face-to-face semester. For course-instructor level analyses, we have 76 instructors teaching 84 business (54) and economics (30) courses at least once in each format.

The control variables are mostly time-invariant. The control variables are Higher Secondary Certificate (HSC) and Secondary School Certificate (SSC) results of the students, sex of the student, sex of the course instructor, number of courses taken each semester, and student's major, annual family income, class size,

[8] The university used the following grading scheme: A (4.0), A- (3.7), B+ (3.3), B (3.0), B- (2.7), C+ (2.3), C (2.0), C- (1.7), D+ (1.3), and D (1.0).

and scholarship recipient. Some studies use demographic characteristics for enrolment biases due to nonminority, older, female students and students with higher GPAs are more likely to enroll in online courses (Xu and Jaggars, 2013). This feature does not apply in this study as the university offers only online or face-to-face classes in a semester. That is, students cannot choose whether they want to take a course online or in face-to-face classes.

(Insert Tables 1 and 2 here)

Tables 1 and 2 present the summary statistics of the outcomes as well as the student, instructor, and course characteristics used in estimating models (1), (2) and (3). As Table 1 shows, about 35 percent of the observations in the student sample come from the online format. The grades are available for students who did not retake or withdraw from a course, a total of 68,151. The whole sample average of grade points is 2.91 on a scale of 0 to 4. The mean grade points in online format is 0.09 points higher than the face-to-face format and statistically significant. Most of the outcome variables have statistically significantly higher values in online classes. The mean values of most of the control variables in the student sample in online and face-to-face formats are statistically significantly different. Table 2 shows a similar pattern for the course level sample. For example, the course level mean of average grade points is higher by 0.08 points and the CV is lower by 0.03 (equivalent to about one standard deviation of 0.09) in online format. The lower CV in the online format may be due to a consistent difference in the grading system and/or cheating. The next section discusses the results of this study. Figure 1 presents students' letter grade distribution including Rs and Ws in online and face-to-face classes. As the figure shows, the share of students receiving poorer grades in online classes is going down while it is going up for better grades indicating better performance in online classes than in face-to-face classes.

(Insert Figure 1 here)

5 Results

To emphasize the importance of the difference in student performance in online and face-to-face formats, we want to start the discussion with two simple graphs presented in Figures 2 and 3. As Figure 2 shows, there is a jump of 0.09 points in average GP in online semesters compared to face-to-face format. This difference is also statistically significant. As discussed earlier, the better performance in online semesters may be because of a consistent difference in grading in online classes, cheating, or a combination of both. Figure 3 presents the kernel density plot of the GP in online and face-to-face classes to visualize the difference. The figure shows that the higher GP in online format comes from a narrower distribution. The density line for online format lies below that of face-to-face at lower GPs and lies above at higher GPs. That is, more students are receiving higher grade points in online format than face-to-face format, indicating a methodical difference in grading. We conduct tests of equality of the variance of GP in two formats. The test statistics reject the null hypothesis of equality, indicating higher variance in the face-to-face format.

(Insert Figures 2 and 3 here)

To examine if these results truly represent the effect of online classes, we estimate equations (1), (2) and (3) using a two-way fixed effects model.

5.1 GP in online vs. face-to-face format

Our primary model for estimating equation (1)–(3) is the fixed effects model. Statistical tests favor this model over OLS and the random-effects model. The estimates of equation (1) are presented in Table 3. Though the preferred model is the fixed effects model, the table reports FE and RE estimates. The estimates from the main specification are presented in columns (3) and (6). The FE estimate of the online effect is 0.208, while the RE estimate is 0.174, quite close to the FE estimate. Our results suggest that the online format increases GP by about 0.21 points. That is, the effect of the online format is large enough to improve student grades by one letter grade as the average GP in face-to-face format is 2.88 points.

(Insert Tables 3 and 4 here)

Next, we look into who benefits most from the change in the instruction format. We reestimate the same models with interaction terms of the online format and students' performance in previous semesters. We construct four dummy variables for the quartiles of lagged CGPA and use the first quartile (poorest performers) as the reference group. The results are presented in Table 4. Both FE and RE estimates show that relatively poor performers benefit from the online format. The coefficient of the online format of the FE model (column 2) is 0.292 and the interaction terms of online and the lagged CGPA quartiles are all negative and statistically significant only for the top two quartiles. These results indicate that the online format increases the GP of the reference group (first quartile) by 0.292 points, almost the opposite of the best performers (-0.301 points). The interaction term for the second quartile is small (-0.023) in magnitude (statistically insignificant) and indicates the students below median benefit the most. Students at the third quartile gain only about half of the bottom quartile's ($0.292 - 0.153 = 0.139$ points). The positive effect of the online format entirely disappears, leading to a null effect of online format on performance for the top quartile.

(Insert Table 5 here)

We also explore the effect of online education on other measures of student performance. These are – if a student (1) withdraws from a course, (2) retakes a course, (3) fails a course (F grade), (3) receives a letter grade of C or better, (4) receives a letter grade of B or better, and (5) receives a letter grade of A- or better. The results are presented in Table 5. The first three columns show that the students are less likely to retake a course or withdraw. Students retake a course to improve their grades. A lower retake rate is expected since we have only four semesters of online classes. A lower withdrawal rate in online classes may bias the effect of online classes on GP which will be addressed in the robustness section. Column (4) shows that students are 4 percentage points more likely to fail a course in online than in face-to-face format. One might interpret this as a negative effect of online classes on student performance. However, this is not the case. When a student fails a course, she/he retakes it expecting a better grade, an F grade is replaced with an R (for retake). Since the last few semesters were the online semesters, students did not have enough time to retake those courses and hence more Fs in online classes than in face-to-face classes. Columns (5), (6) and (7) show that students are more likely to get a better grade (C or better, B or better and A- or better) in online classes confirming the findings in Table 3.

5.2 AGP in online vs. face-to-face format

The estimates of equation (2) are presented in Table 6. Test statistics indicate that the FE model is preferred over OLS and RE models. The table includes both FE and RE estimates for comparison and the effect of online instructions are nearly identical. The main specification in columns (3) and (6) includes both time fixed effect and other control variables. These results suggest that the online format increases AGP by about 0.086 points. So, the estimates of both equations (1) and (2) indicate that the online format increases grades though the estimate from the second equation is low and not large enough to change the letter grade that students receive.

(Insert Tables 6 and 7 here)

5.3 CV of course grade points

As mentioned earlier, better performance in online format compared to face-to-face classes does not necessarily mean better learning. Since online tests are not proctored, students have the opportunity to adopt unfair means (Harmon and Lambrinos, 2008; Fask et al., 2014; Karim et al., 2014; Diedenhofen and Much, 2017; Bilen and Matros, 2021). Online teaching is also new to most teachers in the country, and instructors may still be in the learning phase. Instructors may also want to be lenient during this challenging time of a global crisis. So, a systematic difference in grading may lead to better grades in online classes. We estimate equation (3) to examine if online instruction leads to any change in the spread of the grade distribution, and the results are presented in Table 7. Again, test statistics suggest that the FE model is preferred over OLS and RE models. Similar to equation (2), FE and RE models produce nearly identical estimates of the effect of online format on variation in grade points. The results show that online format reduces CV of course level grade points by about 0.027 points presented in column (3) of Table 7. This estimate is equivalent to a standard deviation of about 0.08 ($= 0.027 \times 2.84$) points. That is, the inflated performance in the online format is the result of a systematic difference in grading.

6 Robustness Check

As pointed out earlier, when students retake a course (R) or withdraw from a course (W), we do not observe their letter grades. Columns (1) – (3) of Table 5 show that the retake and withdrawal rates are significantly lower in online classes. Generally, students retake a course if they perform poorly and withdraw from it if they expect poor performance. Since the Rs and Ws are lower in online classes, our estimates of the online effect on GP may be biased downward. We assume that students retake a course if they receive a poor grade and withdraw from it if they expect a poor grade. We look at the share of students who receive a letter grade of B- or a lower grade (a measure of poor performance) which is about 40 percent. Then, we replace Rs and Ws randomly by the same proportion. For example, the share of students receiving a letter grade of C is about 6.6 percent which is about 16 percent of the 40 percent. Then 16 percent of the Rs and Ws are randomly replaced with a letter grade of C. The results with the reconstructed data set are presented in Table 8 which indicates that our main results in Table 3 probably underestimate the true effect. The results from the main specification presented in column (3) in Table 8 show that the online format increases GP by about 0.264 points which is slightly higher than the main estimate of 0.208 points in Table 3.

(Insert Tables 8 and 9 here)

We conducted the same exercise for the course-instructor sample and the results are presented in Table 9. The estimates from FE and RE models are nearly identical. The estimated effect of online education on AGP is positive as found in Table 6. However, the reported estimates in Table 9 are larger than the estimates in Table 6 (0.137 vs. 0.086). Table 9 reports the effects on CV and the estimate of -0.025 is very similar to the main estimate of -0.027. Notwithstanding, it is reassuring that our main findings of positive effects of online education on student performance coming from a narrower distribution is confirmed in this exercise.

(Insert Tables 10 and 11 here)

We conduct some additional robustness checks. Figure 2 shows that the mean grade points before Fall 2017 are low and exhibit a stable uptrend. So one might argue that results in these three semesters (Fall 2016 to Summer 2017) are quite different from the semesters since Fall 2017 and may cause an upward bias in the main estimate. So we estimate the effect of online education dropping the first three semesters and present the results in Table 10 for the student sample and in Table 11 for the course-instructor sample. We find that the new estimates are very similar to the main estimates (0.186 vs. 0.208 for the student sample and 0.089

vs. 0.086 for the course-instructor sample), but for CV, the new estimates are large in magnitude (-0.044 vs. -0.207). The main conclusion, however, is the same that the higher grades in online format come from a narrower distribution.

Instead of using a single dummy variable for online semesters, we also examine what happened to student grades in online semesters over time using dummy variables for the first to fourth online semester with face-to-face semesters as the reference group. This approach will give us some idea of any learning effects for instructors as they continue to teach online. The course-instructor level results are presented in Table 12. The results show that the gains in online semesters are getting smaller over time (Panel A of Table 12). The effect of the second online semester is 0.121 points, while it is 0.079 in the fourth online semester (Column (2)). Panel B shows that the CV of course level grade points increases over time (negative coefficients with face-to-face as the reference group). As column (2) shows, the CV in the second online semester (compared to face-to-face format) is lower by 0.067 compared to face-to-face classes while in the fourth online semester, it is lower by 0.041. That is, the results in Table 12 indicate potential learning effects for teachers. Teachers are probably formulating questions that are better suited for unproctored tests. However, it is important to acknowledge that these estimates may also capture time-varying fixed effects since we are not controlling for that here.

(Insert Tables 12 – 14 here)

Spring 2020 was the first semester when the university started academic activities online. The first half of the semester was in-person and the second half was online. Since Spring 2020 is a mixture of the two formats, one might object to classifying it as an online semester. So, we drop the observations for Spring 2020 from our sample and examine the effect of online education on student performance. The results for the student sample are presented in Table 13 and the effect of online education is 0.186, close to the main estimate of 0.208. The results for the course-instructor sample are presented in Table 14. The effect of online format on AGP is 0.147 points, larger than the main estimate of 0.086. The effect on variation in grades is nearly identical to the main estimate ($-0.028\ vs.\ -0.027$).

The results in this section suggest a positive effect of online education on student performance. The better grades come from a narrower distribution which may arise from a systematic difference in grading and/or cheating during online semesters. If anything, our main estimates are likely to be biased downward, not upward.

7 Conclusion

The COVID-19 pandemic has forced educational institutions worldwide to move academic activities online and Bangladesh is no exception. It creates a unique opportunity to explore the effect of this technology on the education system in the country. Using students' academic record from a private university in Bangladesh, we examine how online format affect student performance and if there is any systematic difference in grading. We use two-way fixed effects regression models to eliminate entity and time specific unobservable factors that may bias our results.

Our findings suggest that the online format leads to a slight increase in grades, benefiting mostly the poorly performing students. Students at the top quartile of performance distribution do not exhibit any improvement in grade points in the online format. When we focus on the overall course level grade, the online format increases average course level grade points by about 0.086 points which is not large enough to change the average grade. The reduction in variance in grade points may be the result of online collaboration among students, more lenient grading by the instructors due to the pandemic situation or because of using increased group activities for assessment. Our data is not rich enough to address these issues separately in this study. We also find that instructors learns from their online experiences which contributes to the gradual increase in grade point variance during the pandemic period.

Existing literature indicates that cheating in online tests is generally common when carefully studied. As Bilen and Matros (2021) show that cheating in unproctored tests is expected. They suggest camera capturing of the computer screen and the room during the test. Camera capturing may not be an appropriate measure due to the socio-economic condition of Bangladesh. Besides, Karim et al. (2014) show that webcam monitoring increased pressure as well as concerns over privacy. Diedenhofen and Musch (2017) show that generating popup messages asking not to cheat when test-takers change window or browser tab can reduce cheating. This, however, is unlikely to stop students from using a different device or getting any in-person help during an examination.

Though we do not have any direct evidence of the adoption of unfair practices in the online format, we find evidence of higher grade points and a narrower distribution than in the face-to-face format. Any online education programs or course offerings should take this into account. Thus, to ensure that the adoption of unfair practices is not the source of better performance, the online instructions should accompany proctored in-person examinations. Since online education is a convenient way of both delivering and receiving educational services, further studies can be conducted at the national level to explore the effectiveness of online education in learning and formulating policies regarding online education in the country.

Table 1: Summary statistics – students' sample.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Whole sample			Face-to-face		Online		Difference
	Obs	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	[Col(4)-Col(6)]
Grade points	68151	2.91	0.81	2.88	0.83	2.97	0.77	-0.09***
Withdraw	76082	0.06	0.23	0.07	0.25	0.03	0.18	0.03***
Retake	76082	0.05	0.22	0.07	0.26	0.01	0.10	0.06***
Grade: F	68151	0.01	0.08	0.00	0.05	0.01	0.11	-0.01***
Grade: C or better	68151	0.89	0.31	0.88	0.33	0.92	0.27	-0.04***
Grade: B or better	68151	0.60	0.49	0.57	0.50	0.64	0.48	-0.07***
Grade: A- or better	68151	0.24	0.43	0.25	0.43	0.24	0.43	0
Online	76082	0.35	0.48					
Female	76082	0.38	0.49	0.37	0.48	0.40	0.49	-0.03***
Lagged CGPA	69882	2.89	0.51	2.88	0.51	2.90	0.51	-0.02***
Economics Major	76082	0.13	0.34	0.13	0.33	0.13	0.34	-0.01**
Course level 100	76082	0.42	0.49	0.51	0.50	0.26	0.44	0.25***
Course level 200	76082	0.23	0.42	0.23	0.42	0.23	0.42	-0.01
Course level 300	76082	0.17	0.38	0.15	0.36	0.21	0.41	-0.06***
Course level 400	76082	0.18	0.38	0.11	0.32	0.29	0.46	-0.18***
Class Size	76082	38.17	6.35	38.59	6.17	37.37	6.62	1.22***
Age	76082	21.07	1.61	20.66	1.52	21.83	1.50	-1.18***
Annual income (taka)	76082	879361	4211076	864945	4136246	906449	4348153	-41504
Log income	76082	13.19	0.81	13.18	0.81	13.20	0.81	-0.02***
Merit scholarship	76082	0.02	0.15	0.02	0.15	0.03	0.17	-0.01***
Need based scholarship	76082	0.06	0.24	0.05	0.22	0.09	0.29	-0.04***
Other Scholarship	76082	0.02	0.15	0.03	0.16	0.02	0.13	0.01***
Course load	76082	3.28	0.48	3.25	0.45	3.32	0.54	-0.07***
Course load dummy for less than 4 courses	76082	0.72	0.45	0.75	0.43	0.67	0.47	0.08***
GPA in SSC	76082	4.69	0.40	4.69	0.39	4.69	0.40	0
GPA in HSC	76082	4.39	0.51	4.42	0.51	4.34	0.51	0.09***
HSC to admission year gap	76082	1.18	0.66	1.18	0.66	1.16	0.67	0.02**

Notes:
(1) 1 USD = Taka 86 (approximate as of 2021).
(1) *** and ** denote statistical significance at 1% and 5% level of significance, respectively.

Table 2: Summary statistics – course-instructor sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Whole sample			Face-2-face		Online		Difference
	Obs	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	[Col(4)-Col(6)]
Average grade points	2283	2.87	0.30	2.84	0.30	2.92	0.30	-0.08***
CV of grade points	2283	0.29	0.11	0.30	0.11	0.26	0.11	0.03***
Online	2283	0.35	0.48					
Female Instructor	2283	0.46	0.50	0.45	0.50	0.48	0.50	-0.03
Instructor has a Ph.D.	2283	0.20	0.40	0.21	0.41	0.20	0.40	0.01
Course level 100	2283	0.35	0.48	0.33	0.47	0.38	0.49	-0.05*
Course level 200	2283	0.19	0.39	0.18	0.39	0.20	0.40	-0.02
Course level 300	2283	0.20	0.40	0.20	0.40	0.19	0.39	0.01
Course level 400	2283	0.27	0.44	0.29	0.45	0.23	0.42	0.05**
BBA department	2283	0.79	0.41	0.82	0.39	0.73	0.44	0.08***
Economics department	2283	0.21	0.41	0.19	0.39	0.27	0.44	-0.08***
Teaching load	2283	4.06	0.83	4.23	0.89	3.72	0.57	0.51***
Class size	2283	37.23	7.23	37.66	7.25	36.41	7.14	1.26***
Class size: up to 30	2283	0.16	0.37	0.15	0.36	0.19	0.39	-0.03*
Class size: 31-37	2283	0.23	0.42	0.22	0.42	0.25	0.43	-0.03
Class size: 38-42	2283	0.38	0.49	0.38	0.48	0.40	0.49	-0.02
Class size: 43+	2283	0.22	0.42	0.25	0.43	0.17	0.37	0.08***

Notes: ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 3: The effect on student's course level grade points.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Fixed Effects			Random Effects	
Online	0.113***	0.217***	0.208***	0.110***	0.139***	0.174***
	(0.008)	(0.029)	(0.036)	(0.008)	(0.027)	(0.026)
Female						0.068***
						(0.011)
Lagged CGPA			-0.155***			0.641***
			(0.023)			(0.015)
Economics Major						-0.005
						(0.019)
Course level: 200			0.002			0.038*
			(0.020)			(0.021)
Course level: 300			0.058			0.158
			(0.104)			(0.109)
Course level: 400			-0.098			-0.037
			(0.065)			(0.064)
Class size: 31-37			-0.066***			-0.065***
			(0.010)			(0.010)
Class size 38-42			-0.090***			-0.089***
			(0.010)			(0.010)
Class size: above 42			-0.096***			-0.096***
			(0.011)			(0.011)
Age: (19-21] years			0.013			-0.005
			(0.016)			(0.016)
Age: (21-23] years			0.026			-0.014
			(0.022)			(0.018)
Age: (23-25] years			0.027			-0.030
			(0.029)			(0.023)
Age: (25-31] years			0.051			-0.044
			(0.057)			(0.049)
Log income						-0.015**
						(0.007)
Merit Scholarship			0.017			0.102***
			(0.022)			(0.020)
Need based scholarship			-0.033***			0.036***
			(0.013)			(0.012)
Other scholarship			0.012			0.039
			(0.040)			(0.029)
Course load: Up to 3 courses			0.009			-0.011*
			(0.007)			(0.007)
GPA in SSC						0.074***
						(0.017)
GPA in HSC						0.125***
						(0.013)
HSC to Admission year gap						-0.003
						(0.009)
Constant	2.871***	2.686***	3.268***	2.792***	2.679***	0.175

	(0.003)	(0.082)	(0.089)	(0.011)	(0.083)	(0.136)
Observations	63,126	63,126	63,126	63,126	63,126	63,126
R-squared	0.007	0.110	0.113			
Time FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	Yes	Yes	No	Yes	Yes
Instructor FE	No	Yes	Yes	No	Yes	Yes
Number of students	3,197	3,197	3,197	3,197	3,197	3,197

Notes:
(1) Clustered standard errors are in parentheses.
(2) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 4: The effect on student's course level grade points interacted with quartiles of lagged CGPA.

Variables	(1)	(2)	(3)	(4)
	Fixed Effects		Random Effects	
Online	0.297***	0.292***	0.169***	0.221***
	(0.034)	(0.039)	(0.031)	(0.032)
2nd quartile of lagged CGPA	-0.089***	-0.087***	0.213***	0.198***
	(0.016)	(0.016)	(0.016)	(0.016)
3rd quartile of lagged CGPA	-0.094***	-0.091***	0.540***	0.504***
	(0.021)	(0.021)	(0.018)	(0.018)
4th quartile of lagged CGPA	-0.081***	-0.077***	0.914***	0.834***
	(0.025)	(0.025)	(0.019)	(0.019)
Online X 2nd quartile	-0.021	-0.023	0.025	0.023
	(0.022)	(0.022)	(0.022)	(0.022)
Online X 3rd quartile	-0.150***	-0.153***	-0.078***	-0.081***
	(0.022)	(0.021)	(0.022)	(0.021)
Online X 4th quartile	-0.296***	-0.301***	-0.192***	-0.215***
	(0.020)	(0.020)	(0.021)	(0.020)
Observations	63,126	63,126	63,126	63,126
Number of students	3,197	3,197	3,197	3,197
Time FE	Yes	Yes	Yes	Yes
Course FE	Yes	Yes	Yes	Yes
Instructor FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes:
(1) Control variables include age, sex, major, scholarship status, SSC and HHS GPA of the student, course level, class size, semester course load, lagged CGPA, monthly household income, and HSC to admission year gap.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 5: The effects of online format on other measures of student performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variables →	Withdraw from a course	Retake a course	Withdraw or Retake	Grade: F	Grade: C or better	Grade: B or better	Grade: A- or better
Fixed Effects	-0.101***	-0.141***	-0.243***	0.040***	0.031**	0.191***	0.119***
	(0.011)	(0.012)	(0.015)	(0.005)	(0.015)	(0.022)	(0.018)
Random Effects	-0.039***	-0.117***	-0.156***	0.036***	0.048***	0.138***	0.043***

	(0.007)	(0.009)	(0.011)	(0.004)	(0.011)	(0.015)	(0.013)
Observations	69,882	69,882	69,882	63,126	63,126	63,126	63,126
Number of students	3,200	3,200	3,200	3,197	3,197	3,197	3,197
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instructor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes:
(1) Control variables include age, sex, major, scholarship status, SSC and HHS GPA of the student, course level, class size, semester course load, lagged CGPA, monthly household income, and HSC to admission year gap.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 6: The effect on course level average grade points (AGP).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
Online	0.114***	0.102***	0.086**	0.109***	0.091**	0.083**
	(0.016)	(0.037)	(0.039)	(0.016)	(0.036)	(0.038)
Female						-0.030
						(0.027)
Instructor has a Ph.D.						-0.032
						(0.035)
Course level: 200						0.076**
						(0.037)
Course level: 300						0.186***
						(0.036)
Course level: 400						0.175***
						(0.040)
Course offering department: Economics						-0.074**
						(0.032)
Teaching load: 4 courses			-0.033*			-0.028
			(0.019)			(0.018)
Teaching load: 5+ courses			-0.037			-0.023
			(0.026)			(0.025)
Class size 31-37			-0.018			-0.017
			(0.020)			(0.020)
Class size 38-42			0.008			0.013
			(0.022)			(0.021)
Class size 43+			0.035			0.043*
			(0.024)			(0.023)
Constant	2.825***	2.811***	2.841***	2.816***	2.804***	2.767***
	(0.006)	(0.027)	(0.036)	(0.016)	(0.031)	(0.049)
Observations	2,283	2,283	2,283	2,283	2,283	2,283
R-squared	0.050	0.062	0.068			
Time FE	No	Yes	Yes	No	Yes	Yes

Course FE	No	No	No	No	No	No
Number of course-instructor combinations	212	212	212	212	212	212

Notes:
(1) AGP is the class average of grade points in a course.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 7: The effect on course level coefficient of variation (CV) of grade points.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
Online	-0.048***	-0.028**	-0.027**	-0.046***	-0.025**	-0.026**
	(0.006)	(0.011)	(0.012)	(0.006)	(0.011)	(0.011)
Female						0.026***
						(0.009)
Instructor has a Ph.D.						0.009
						(0.012)
Course level: 200						-0.032***
						(0.012)
Course level: 300						-0.077***
						(0.012)
Course level: 400						-0.076***
						(0.013)
Course offering department: Economics						0.060***
						(0.011)
Teaching load: 4 courses			0.006			0.005
			(0.006)			(0.005)
Teaching load: 5+ courses			0.001			-0.002
			(0.007)			(0.007)
Class size 31-37			-0.008			-0.010
			(0.008)			(0.008)
Class size 38-42			-0.018**			-0.022***
			(0.007)			(0.007)
Class size 43+			-0.033***			-0.038***
			(0.008)			(0.008)
Constant	0.303***	0.292***	0.303***	0.311***	0.299***	0.323***
	(0.002)	(0.007)	(0.011)	(0.006)	(0.009)	(0.016)
Observations	2,283	2,283	2,283	2,283	2,283	2,283
R-squared	0.076	0.082	0.095			
Time FE	No	Yes	Yes	No	Yes	Yes
Number of course-instructor combinations	212	212	212	212	212	212

Notes:
(1) CV is the coefficient of variation of grade points in a course.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 8: The effect of online format on student performance (replacing Ws and Rs).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
Online	0.155***	0.341***	0.264***	0.155***	0.251***	0.224***
	(0.008)	(0.028)	(0.034)	(0.008)	(0.026)	(0.024)
Female						0.070***
						(0.011)
Lagged CGPA			-0.055***			0.631***
			(0.021)			(0.015)
Economics Major						0.008
						(0.018)
Course level: 200			-0.010			0.028
			(0.019)			(0.020)
Course level: 300			-0.029			0.069
			(0.101)			(0.107)
Course level: 400			-0.148**			-0.073
			(0.066)			(0.066)
Class size: 31-37			-0.062***			-0.058***
			(0.010)			(0.010)
Class size 38-42			-0.085***			-0.079***
			(0.010)			(0.010)
Class size: above 42			-0.085***			-0.079***
			(0.011)			(0.011)
Age: (19-21] years			0.016			-0.004
			(0.016)			(0.015)
Age: (21-23] years			0.033			-0.009
			(0.021)			(0.018)
Age: (23-25] years			0.036			-0.026
			(0.029)			(0.023)
Age: (25-31] years			0.046			-0.027
			(0.057)			(0.045)
Log income						-0.013*
						(0.007)
Merit Scholarship			-0.002			0.140***
			(0.023)			(0.020)
Need based scholarship			-0.054***			0.056***
			(0.013)			(0.013)
Other scholarship			-0.000			0.022
			(0.040)			(0.031)
Course load: Up to 3 courses			-0.006			-0.030***
			(0.007)			(0.007)
GPA in SSC						0.055***
						(0.016)
GPA in HSC						0.125***
						(0.012)
HSC to Admission year gap						-0.008
						(0.009)
Constant	2.772***	2.494***	2.933***	2.735***	2.538***	0.273**
	(0.003)	(0.081)	(0.082)	(0.010)	(0.081)	(0.129)

Observations	76,082	76,082	69,882	76,082	76,082	69,882
Number of students	3,200	3,200	3,200	3,200	3,200	3,200
Time FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	Yes	Yes	No	Yes	Yes
Instructor FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes:
(1) Sample includes observations with missing grade points due to Rs and Ws. We randomly replace Rs and Ws with B- or a lower grade at the same proportion as found in the existing data. For example, the share of students receiving a letter grade of C is about 6.6 percent which is about 16 percent of the students receiving a grade less than B. So, 16 percent of the Rs and Ws are randomly replaced with a letter grade of C.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 9: The effect of online format on AGP and CV (replacing Rs and Ws).

Dep. Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
AGP	0.148***	0.151***	0.137***	0.144***	0.142***	0.134***
	(0.017)	(0.035)	(0.036)	(0.016)	(0.034)	(0.035)
CV of Grade Points	-0.047***	-0.026**	-0.025**	-0.045***	-0.023**	-0.023**
	(0.006)	(0.011)	(0.010)	(0.006)	(0.011)	(0.010)
Observations	2,283	2,283	2,283	2,283	2,283	2,283
Number panel entity	212	212	212	212	212	212
Time FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes:
(1) AGP is the class average of grade points in a course.
(2) CV is the coefficient of variation of grade points in a course.
(3) Sample includes observations with missing grade points due to Rs and Ws. We randomly replace the Rs and Ws with B- or a lower grade at the same proportion as found in the existing data. For example, the share of students receiving a letter grade of C is about 6.6 percent which is about 16 percent of the students receiving a grade less than B. So, 16 percent of the Rs and Ws are randomly replaced with a letter grade of C.
(4) Control variables include sex of the instructor, if instructor has a PhD, 3 dummy variables for 200, 300 and 400 level courses (100 level as the base category), dummy variable for economics department (0 for BBA), 2 dummy variables for teaching load, and three dummy variables for class size.
(5) Clustered standard errors are in parentheses.
(6) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 10: The effect on student's course level grade points (modified sample).

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Fixed Effects			Random Effects		
Online	0.110***	0.191***	0.186***	0.106***	0.119***	0.113***
	(0.008)	(0.023)	(0.030)	(0.008)	(0.022)	(0.021)
Female						0.070***
						(0.011)
Lagged CGPA			-0.199***			0.658***
			(0.026)			(0.016)
Economics Major						-0.007
						(0.019)

Course level: 200			0.008			0.043*
			(0.022)			(0.023)
Course level: 300			0.114			0.208*
			(0.104)			(0.110)
Course level: 400			-0.075			-0.013
			(0.065)			(0.066)
Class size: 31-37			-0.040***			-0.039***
			(0.009)			(0.010)
Class size 38-42			-0.040***			-0.044***
			(0.009)			(0.009)
Class size: above 42			-0.035***			-0.033***
			(0.010)			(0.010)
Age: (19-21] years			0.021			0.006
			(0.017)			(0.017)
Age: (21-23] years			0.035			-0.002
			(0.023)			(0.020)
Age: (23-25] years			0.040			-0.018
			(0.030)			(0.024)
Age: (25-31] years			0.064			-0.040
			(0.055)			(0.049)
Log income						-0.015**
						(0.007)
Merit Scholarship			0.014			0.096***
			(0.023)			(0.021)
Need based scholarship			-0.041***			0.032***
			(0.013)			(0.012)
Other scholarship			0.016			0.046
			(0.041)			(0.031)
Course load: Up to 3 courses			0.004			-0.015**
			(0.007)			(0.007)
GPA in SSC						0.070***
						(0.017)
GPA in HSC						0.121***
						(0.013)
HSC to Admission year gap						-0.005
						(0.009)
Constant	2.876***	2.725***	3.376***	2.796***	2.710***	0.174
	(0.003)	(0.082)	(0.094)	(0.011)	(0.082)	(0.135)
Observations	59,424	59,424	59,424	59,424	59,424	59,424
Student FE	Yes	Yes	Yes	No	No	No
Time FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	Yes	Yes	No	Yes	Yes
Instructor FE	No	Yes	Yes	No	Yes	Yes
Number of students	3,197	3,197	3,197	3,197	3,197	3,197

Notes:
(1) Sample includes observations from Fall 2017 to Spring 2021 and drops the observations from prior semesters.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 11: The effect on course level AGP and CV – modified sample.

Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
AGP	0.111***	0.093***	0.089**	0.106***	0.083**	0.085**
	(0.016)	(0.035)	(0.038)	(0.016)	(0.034)	(0.037)
CV of Grade Points	-0.050***	-0.042***	-0.044***	-0.048***	-0.039***	-0.042***
	(0.006)	(0.012)	(0.013)	(0.006)	(0.012)	(0.012)
Observations	1,925	1,925	1,925	1,925	1,925	1,925
Number panel entity	212	212	212	212	212	212
Time FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes:
(1) AGP is the class average of grade points in a course.
(2) CV is the coefficient of variation of grade points in a course.
(3) Sample includes observations from Fall 2017 to Spring 2021 and drops the observations from prior semesters.
(4) Control variables include sex of the instructor, if instructor has a PhD, 3 dummy variables for 200, 300 and 400 level courses (100 level as the base category), dummy variable for economics department (0 for BBA), 2 dummy variables for teaching load, and three dummy variables for class size.
(5) Clustered standard errors are in parentheses.
(6) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 12: Learning effect model (base category = face-to-face).

Variables	(1)	(2)	(3)	(4)
	Fixed Effects		Random Effects	
Panel A: Dependent variable is AGP and reference category is face-to-face format.				
First online semester	0.125***	0.120***	0.121***	0.119***
	(0.019)	(0.019)	(0.019)	(0.019)
Second online semester	0.121***	0.121***	0.114***	0.121***
	(0.022)	(0.023)	(0.021)	(0.022)
Third online semester	0.123***	0.119***	0.120***	0.122***
	(0.024)	(0.024)	(0.024)	(0.024)
Fourth online semester	0.085***	0.079***	0.078***	0.076***
	(0.026)	(0.026)	(0.026)	(0.026)
Panel B: Dependent variable is CV and reference category is face-to-face format.				
First online semester	-0.042***	-0.041***	-0.040***	-0.040***
	(0.006)	(0.006)	(0.006)	(0.006)
Second online semester	-0.060***	-0.067***	-0.059***	-0.067***
	(0.007)	(0.007)	(0.007)	(0.007)
Third online semester	-0.050***	-0.053***	-0.049***	-0.054***
	(0.008)	(0.008)	(0.008)	(0.008)
Fourth online semester	-0.039***	-0.041***	-0.037***	-0.039***
	(0.010)	(0.010)	(0.010)	(0.009)
Observations	2,283	2,283	2,283	2,283

Number of course-instructor combinations	212	212	212	212
Controls	No	Yes	No	Yes

Notes:
(1) AGP is the class average of grade points in a course.
(2) CV is the coefficient of variation of grade points in a course.
(3) Control variables include sex of the instructor, if instructor has a PhD, 3 dummy variables for 200, 300 and 400 level courses (100 level as the base category), dummy variable for economics department (0 for BBA), 2 dummy variables for teaching load, and three dummy variables for class size.
(4) Clustered standard errors are in parentheses.
(5) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 13: Modified student sample: The effect on student performance.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Fixed Effects			Random Effects	
Online	0.114***	0.204***	0.186***	0.113***	0.133***	0.178***
	(0.009)	(0.030)	(0.038)	(0.009)	(0.027)	(0.027)
Female						0.073***
						(0.012)
Lagged CGPA			-0.137***			0.637***
			(0.024)			(0.016)
Economics Major						0.003
						(0.020)
Course level: 200			0.004			0.041*
			(0.021)			(0.022)
Course level: 300			0.033			0.062
			(0.134)			(0.132)
Course level: 400			-0.135*			-0.077
			(0.071)			(0.071)
Class size: 31-37			-0.071***			-0.068***
			(0.011)			(0.011)
Class size 38-42			-0.095***			-0.091***
			(0.011)			(0.011)
Class size: above 42			-0.096***			-0.093***
			(0.012)			(0.012)
Age: (19-21] years			0.028			-0.006
			(0.017)			(0.016)
Age: (21-23] years			0.048**			-0.018
			(0.023)			(0.019)
Age: (23-25] years			0.051			-0.042*
			(0.032)			(0.025)
Age: (25-31] years			0.078			-0.056
			(0.062)			(0.050)
Log income						-0.015**
						(0.007)
Merit Scholarship			0.013			0.109***
			(0.023)			(0.021)
Need based scholarship			-0.038***			0.042***
			(0.013)			(0.013)

Other scholarship			0.030			0.047
			(0.042)			(0.031)
Course load: Up to 3 courses			0.014*			-0.008
			(0.007)			(0.007)
GPA in SSC						0.070***
						(0.017)
GPA in HSC						0.119***
						(0.014)
HSC to Admission year gap						-0.005
						(0.010)
Constant	2.873***	2.698***	3.259***	2.806***	2.687***	0.288**
	(0.003)	(0.088)	(0.093)	(0.011)	(0.088)	(0.140)
Observations	55,639	55,639	55,639	55,639	55,639	55,639
R-squared	0.006	0.112	0.115			
Time FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	Yes	Yes	No	Yes	Yes
Instructor FE	No	Yes	Yes	No	Yes	Yes
Number of students	3,177	3,177	3,177	3,177	3,177	3,177
Controls	No	No	Yes	No	No	Yes

Notes:
(1) Spring 2020 (mixed mode semester) is dropped.
(2) Clustered standard errors are in parentheses.
(3) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 14: Modified course-instructor sample - the effect on course level AGP and CV.

Dep. Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
AGP	0.154***	0.158***	0.147***	0.149***	0.145***	0.141***
	(0.019)	(0.035)	(0.036)	(0.019)	(0.035)	(0.035)
CV	-0.050***	-0.028**	-0.028***	-0.048***	-0.024**	-0.025**
	(0.007)	(0.011)	(0.011)	(0.007)	(0.011)	(0.010)
Observations	2,062	2,062	2,062	2,062	2,062	2,062
Time FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Number of course-instructor combinations	212	212	212	212	212	212

Notes:
(1) AGP is the class average of grade points in a course.
(2) CV is the coefficient of variation of grade points in a course.
(3) Spring 2020 (mixed mode semester) is dropped.
(4) Control variables include sex of the instructor, if instructor has a PhD, 3 dummy variables for 200, 300 and 400 level courses (100 level as the base category), dummy variable for economics department (0 for BBA), 2 dummy variables for teaching load, and three dummy variables for class size.
(5) Clustered standard errors are in parentheses.
(5) ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Figure 1: The distribution of letter grades in face-to-face and online modes

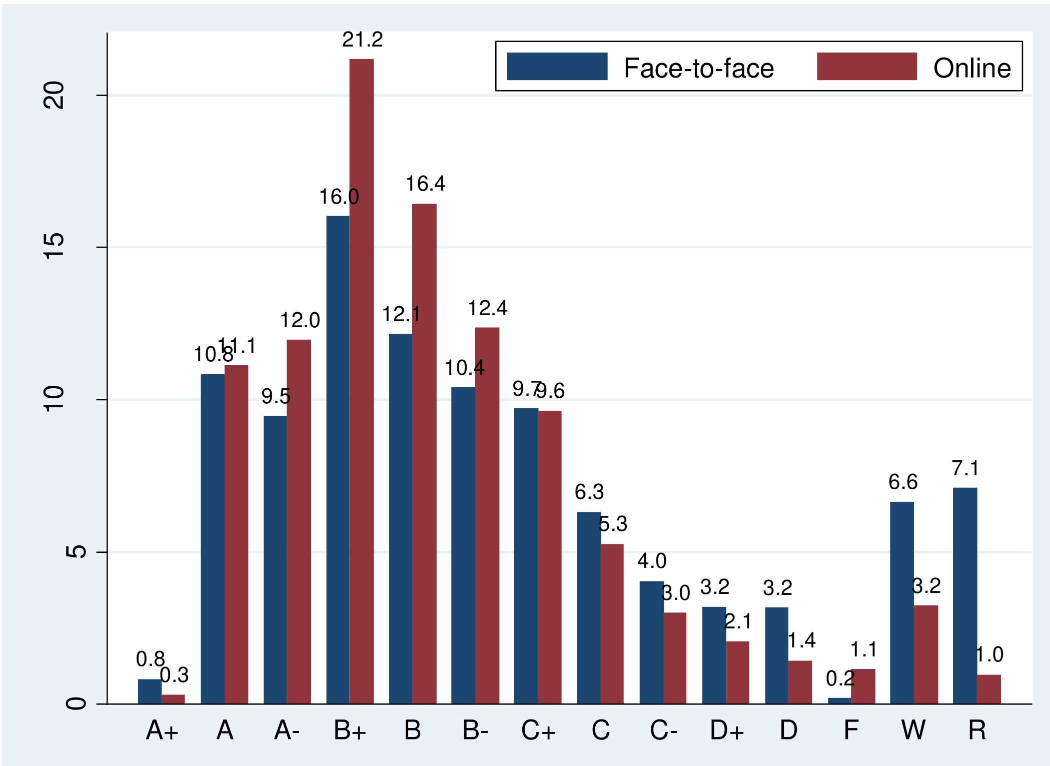


Figure 2: Average grade points in online and face-to-face formats.

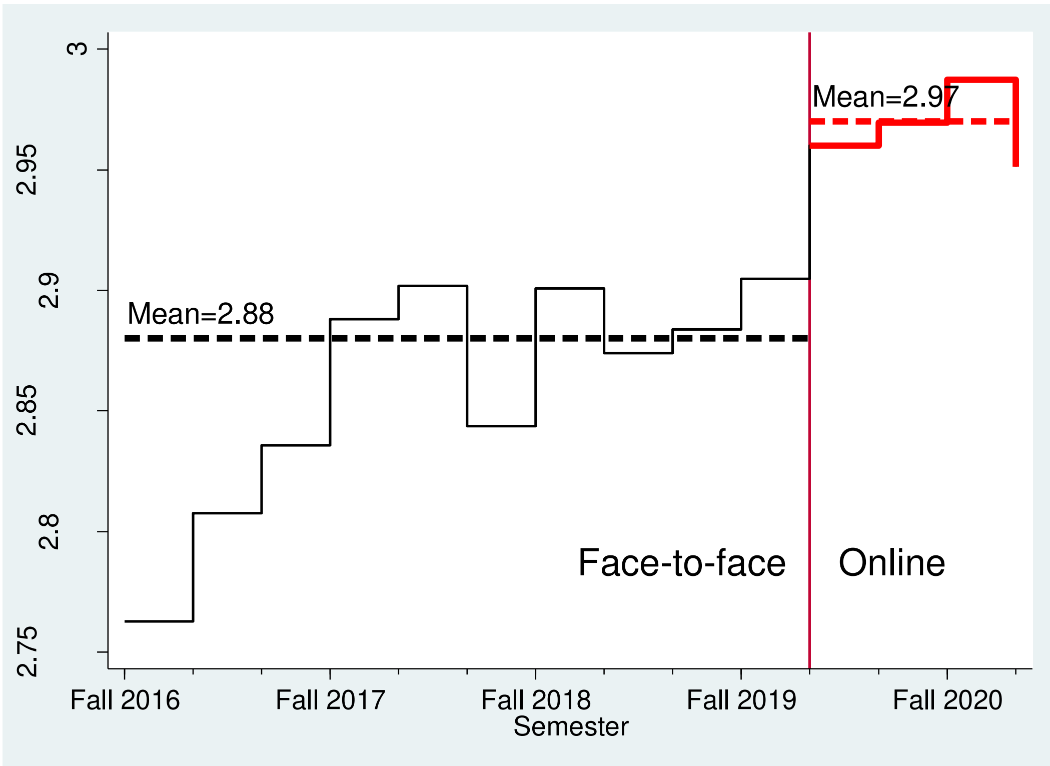
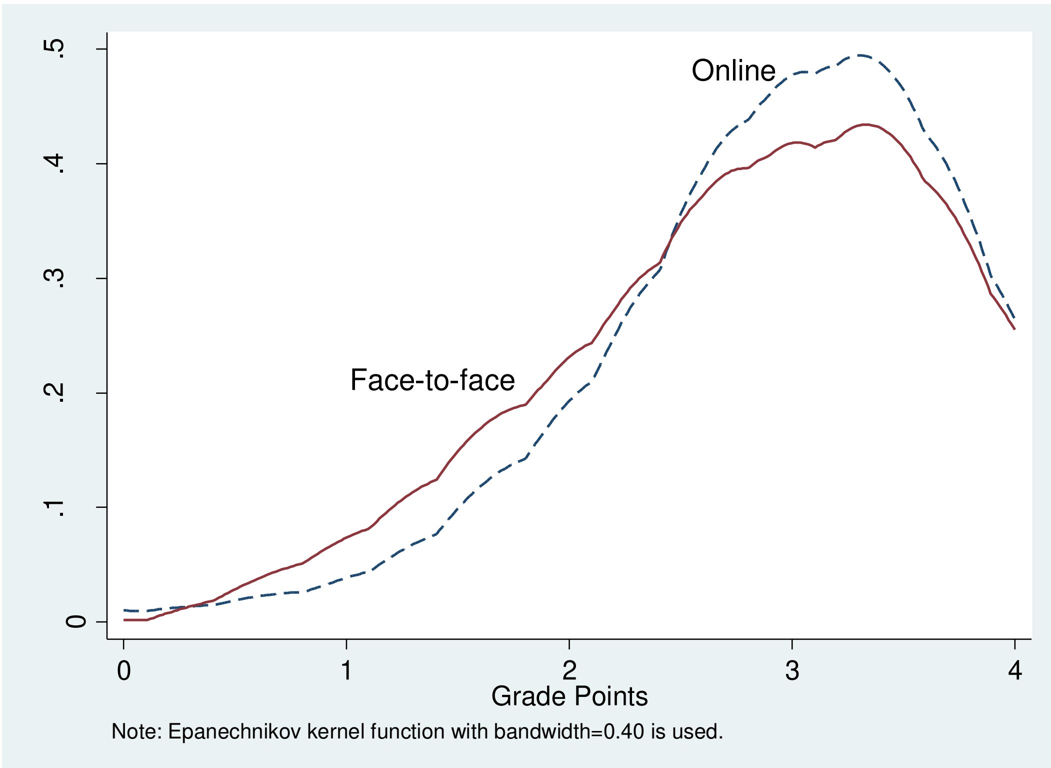


Figure 3: Density plots of grade points in online and face-to-face formats.



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