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

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The COVID-19 pandemic has forced educational institutions in Bangladesh to adopt online technology for higher education in just a couple of months, which otherwise would have taken years. This change creates a unique opportunity to examine student performance in online education. In addition to examining the effect of online education on student performance, this paper investigates if there is a systematic difference in grading. Transcript-level academic records of Business and Economics students from one of the leading private universities in Bangladesh for pre-pandemic and pandemic periods have been used in this paper. The multilevel nested panel structure of the data allows the elimination of individual, time, course, and instructor-level fixed effects that may bias the findings of the study. The results show that student-level grade points in online format are higher by about 0.208 (on a scale of 0 to 4) compared to student-level grade points in face-to-face format. This increase in grade points in the online format is driven by poorly performing students. Course level estimates show that the average grade points (AGP) increase by about 0.086 in the online format, which comes from a narrower distribution, indicating a systematic difference in grading in the online format.

Keywords: COVID-19, Education, Online Education, Student Performance, Cheating, Bangladesh

JEL Classification: A20, I21, I23

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I. INTRODUCTION

The COVID-19 pandemic has changed the education system in Bangladesh beyond recognition. It has forced 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 one in three students takes at least one online course at the higher education level in the United States (Allen & Seaman, 2013). Though Bangladesh did not have any online programs prior to the pandemic, some distance-learning programs were offered by the Bangladesh Open University (BOU). However, these programs are not part of the mainstream education system. As Ali, Haque, and Rumble (1997) pointed out, the target population of BOU includes those who are currently excluded from the mainstream education system.

During the pandemic, most private universities and a few public universities in Bangladesh have adopted online technology to continue academic activities. The online teaching format may vary from one university to another. The university in this study used a synchronous format where teachers and students meet in a virtual classroom using an online platform such as Google Meet and Zoom at the scheduled time, just like the traditional classes. Some of the teachers record their class and share it with students. Some instructors use Google Forms or similar platforms to conduct tests online, while others share questionnaires and collect responses through email or Google Classroom. 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, Chingos, Lack & Nygren, 2014; Means, Toyama, Murphy, Bakia, & Jones, 2009; Bell & Federman, 2013). For example, using a randomised experiment, Bowen et al. (2014) measured 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 standardised assessment of statistical literacy.

On the other hand, some studies show that online education adversely affects student performance compared to face-to-face instruction. Some randomised experiments at US universities for introductory microeconomics courses show that students perform poorly in online classes compared to face-to-face and blended formats (Alpert, Couch, & Harmon, 2016; Figlio, Rush, & Yin, 2013). Using an instrumental variable method, Bettinger, Fox, Loeb, and Taylor (2017) 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. 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.[1] Some studies explore whether 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) do not find any such evidence in a similar setting. Watson and Sottile (2010), using self-reported data on cheating in examinations, conclude that students did not cheat in online tests. Using a game-theoretic approach, Bilen and Matros (2021) show that cheating should be expected in online examinations. They also provide evidence of cheating in online examinations using data from a large private university in the US. Fask, Englander, and Wang (2014) randomly assigned the students to a face-to-face or online format for the final examination and provided suggestive evidence of cheating in the online examination. Diedenhofen and Musch (2017), using a PageFocus program to detect if the test takers switch to different pages while taking the test, find that test takers are more likely to cheat when performance-based incentives are offered. Karim, Kaminsy, and Behrend (2014) conducted an experiment using Amazon's MTruck platform to recruit test takers. They 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. In a field experiment, Vazquez, Chiang, and Sarmiento-Barbieri (2021) found that students in uproctored exams scored 11 per cent higher than those proctored exam participants. They also show that face-to-face proctoring is

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

more effective than online proctoring. Dench and Joyce (2022), using a randomised experiment, also find that students do cheat in submitting online assignments. So, most of the studies, except for the self-reported studies, indicate that students are more likely to adopt unfair practices in unproctored environments.

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 instruction, such as asynchronous, partially asynchronous, blend/hybrid, and flipped classroom mode. The format of online instructions followed by the university in this study does not conform to any of these versions. Rather, it can be classified as "synchronous mode," where teachers meet students online during scheduled class time, just like face-to-face classes. Apart from the different versions of online education, there are also differences in estimation techniques used in different studies, which 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. This change also accompanies the concerns of the educationists in the country that students may adopt unfair means in tests. 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 systematic differences in grading between the two formats, which may result from multiple factors such as teachers and students coping with the new technology and students adopting unfair practices. Identifying the true effects of the online format is difficult since some characteristics that may determine student performance in online education are not observable to the researchers. For example, students may differ from one another in terms of their tech skills to cope with the new technology. Even the quality of internet connections may be different for different students. We employ nested panel data models to eliminate any individual, time, course, and instructor-specific effects from the estimates 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. In order to eliminate the unobserved heterogeneity among students, courses, and course instructors, we include student, course, and instructor-fixed effects in our empirical models. Results from student-level analysis show that the online format increases students' course grade points. 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. 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. In other words, our results 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, this paper would be the first to provide any evidence on how online education affects student performance in Bangladesh.[2] Second, we use a large data set of administrative records of students' academic achievement instead of one or two course-based analyses 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 organised as follows. Section II discusses the conceptual framework, while Section III lays out the empirical strategy of this study. Section IV discusses the data and the summary statistics. Section V presents the results of the study, followed by robustness checks in Section VI. Section VII highlights the main findings and concludes the paper with some policy recommendations.

II. CONCEPTUAL FRAMEWORK

At this early stage, online education in Bangladesh could face many challenges affecting students' academic achievement. These challenges could 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. Here, performance is defined as their grade points. Though higher grade points are generally associated with better learning outcomes, this may not necessarily be true in the absence of appropriate test-taking environments, quality tests, and proper grading.

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 et al., 2013),

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[2]Given the overwhelming preponderance of the US based studies, this research would add value to the literature.

while others find a null effect (Bowen et al., 2014; Means et al., 2009; Bell & Federman, 2013). 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.

Estimating the effect of online education requires a proper understanding of the potential challenges and advantages of online education in Bangladesh. Some of the challenges that may negatively affect student performance include relatively poor IT infrastructure[3], difficulty in coping with new delivery mechanisms (faced by both students and teachers), and not owning the necessary devices for online education. Besides, the lack of peer-to-peer interactions among students that come with 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 & Duflo, 2014).

There are some advantages of online education as well. Online classes can eliminate travel costs almost completely, 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 the average driving speed in Dhaka city has dropped to 7 kilometres per hour (Bird, Li, Rahman, Rama, & Venables, 2018). So, online classes help students save time, energy, and money that can be used for study purposes. Other factors that may positively affect grades are leniency in grading (during the pandemic period), grading format, and adopting unfair practices.

Teachers might become lenient in grading during the pandemic considering the fact that everyone is going through a tough time. 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. Students can 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

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[3]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 a 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

the positive impact of saved travel time dominating negative factors. Student performance in an online format may also depend on the subject matter. For example, the outcome of recalling information or computational testing skills could yield different results than testing conceptual grasp or problem-solving abilities (McPherson & Bacow, 2015).

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 the online format leads to a narrower distribution of 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.

III. 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 an 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 the 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, I_i, C_c, and T_s represent student, instructor, course, and time-fixed effects, respectively, and X' is a vector of other covariates, and e is the error term.

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

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

In models (2) and (3), $\mathrm{AGP}_{\mathrm{cst}}$ and CV_{sct} represent average grade points and coefficient of variation of the grade points, respectively, 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 u and v are the corresponding error terms.

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. The value of θ_2 indicates if the online format leads to a systematic difference in grading. The shift to an online format was completely exogenous, 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, some factors might affect student performance differently 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 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, instructor, and time-fixed effects wherever appropriate in models (1), (2), and (3).

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 behaviour 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. Second, we can examine not only the impact on course-wise student performance but also the average grade points in a course. Finally, 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.

IV. DATA

We use administrative student records from one of the leading private universities in Bangladesh (henceforth the university). 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 the university closure at the beginning of the pandemic. The university tries to follow a common assessment technique – two midterms, final exams, and other assessment methods such as quizzes, homework assignments, etc. The midterms and the final examinations generally account for most of the course grades. The online classes are conducted in "synchronous mode," and the online tests are unproctored. The university has been conducting academic activities online since mid-spring 2020.

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[4] 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 administrative records of student performance are likely to be more accurate than students' self-reported data. For example, adopting unfair means (that may contribute to better grades) is not a socially desirable practice, and hence, if asked, students may underreport it. It is also possible that they overstate their own performance. Overall, self-reported data may contain significant measurement errors.

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. When students graduate, they drop out of the sample. That is, we have an unbalanced panel of students that includes only those enrolled in at least one online semester and one face-to-face semester. For course-

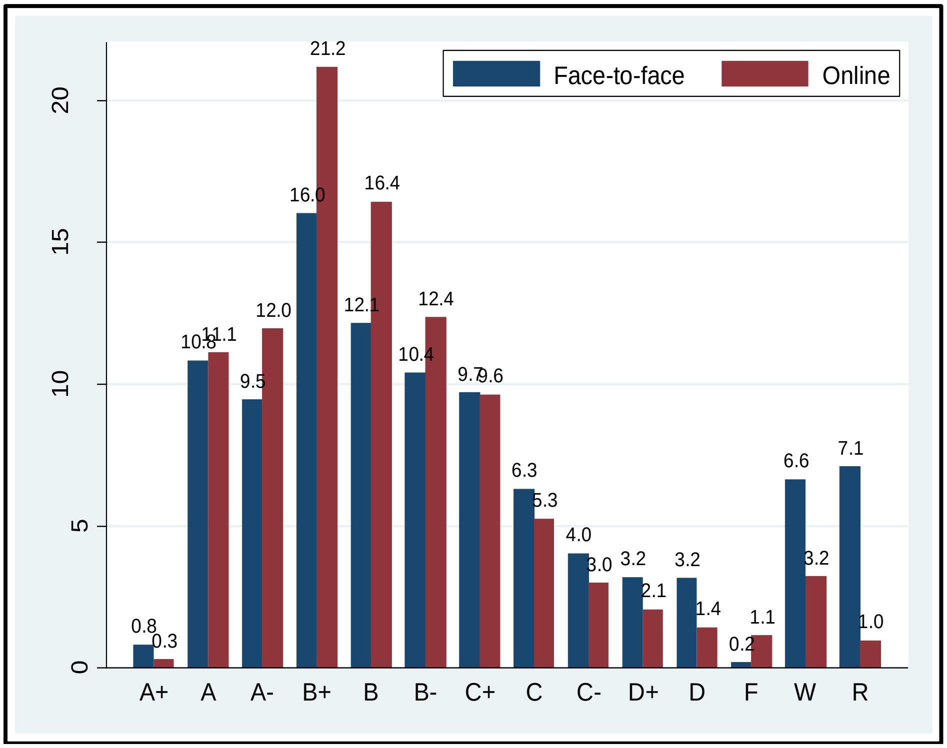
[4]The university used the following grading scheme: A (4.0), A- (3.7), B+ (3.3), B (3.0), B- (2.7), C+ (2.3), C (2.0), C- (1.7), D+ (1.3), and D (1.0).

instructor level analyses, we have an unbalanced panel of 84 business (54) and economics (30) courses taught by 76 instructors at least once in each format.

The control variables are mostly time-invariant; these variables include the Higher Secondary Certificate (HSC) and the Secondary School Certificate (SSC) results of the students, the sex of the student and the course instructor, the number of courses taken each semester, and the student's major, annual family income, class size, and scholarship recipient status. Some studies use demographic characteristics for enrolment biases because nonminority, older, female students and students with higher GPAs are more likely to enrol in online courses (Xu & Jaggars, 2013). This feature does not apply in this study as the university offers only online or face-to-face classes in a semester.

The summary statistics of the outcomes, as well as the student, instructor, and course characteristics used in estimating models (1), (2), and (3), are available in the appendix. The data show that about 35 per cent 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 the online format are 0.09 points higher than in 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. The data also show 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. 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.

FIGURE 1: **The Distribution of Letter Grades in Face-to-Face and Online Formats**



V. RESULTS

To emphasise the importance of the difference in student performance in online and face-to-face formats, we start the discussion with two simple graphs, as 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 a face-to-face format, which is statistically significant. As discussed earlier, it may be due to differences in grading style, more cheating in online tests, or a combination of both. Figure 3 presents the kernel density plots of the GP and shows that the higher GP in the 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 receive higher grade points in online format than in face-to-face format. 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.

FIGURE 2: **Average Grade Points in Online and Face-to-Face Formats**

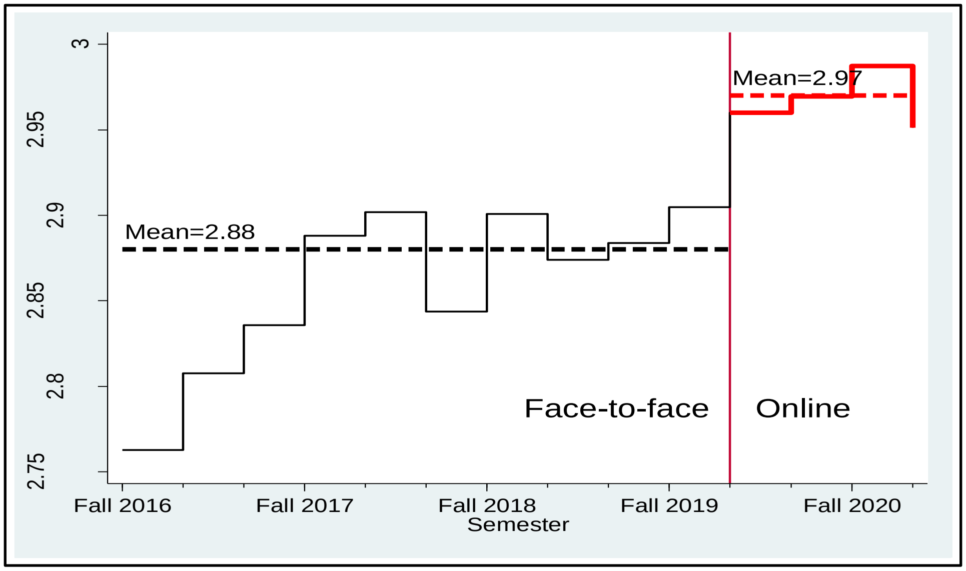
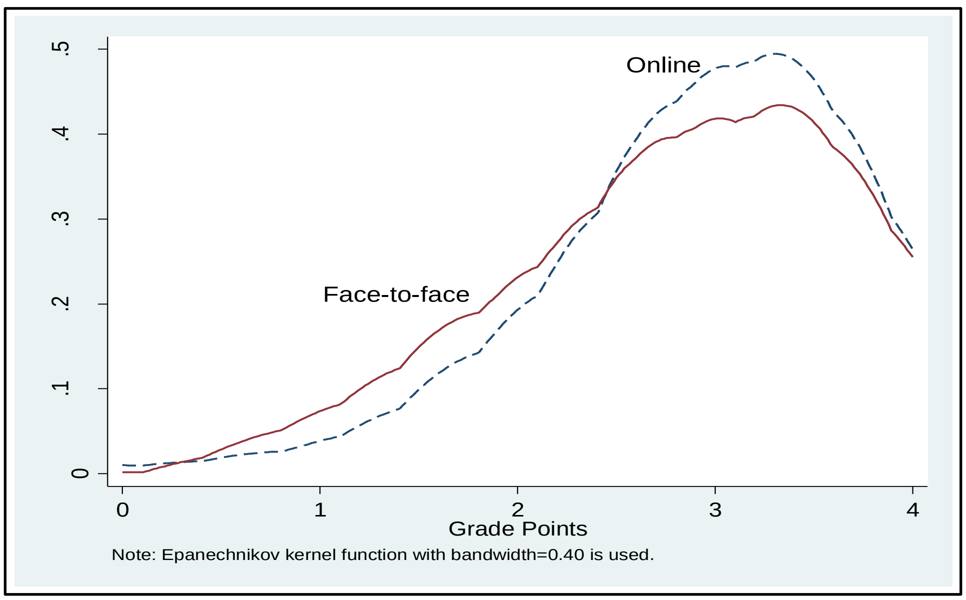


FIGURE 3: **Density Plots of the Grade Points in Online and Face-to-Face Formats**



To examine if these results truly represent the effect of online classes, we estimate equations (1), (2), and (3) using nested panel data models.

5.1 GP in Online vs. Face-to-Face Format

Our primary model for estimating equations (1)–(3) is the fixed effects (FE) model. The estimates of equation (1) are presented in Table I (due to space limitation, additional results are put in the appendix). The Hausman specification tests reject the null hypothesis that the random effects (RE) estimates are efficient and consistent, favouring the FE models. However, we present both FE and RE estimates for comparison. 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, which is 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.

TABLE I

THE EFFECT OF ONLINE FORMAT ON STUDENTS' COURSE LEVEL GRADE POINTS

Dep. Var ↓	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
Grade points	0.113***	0.217***	0.208***	0.110***	0.139***	0.174***
(online vs. face-to-face)	(0.008)	(0.029)	(0.036)	(0.008)	(0.027)	(0.026)
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) Control variables include age, sex, major, scholarship status, SSC and HSC 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 II

THE EFFECT ON STUDENTS' COURSE LEVEL GRADE POINTS INTERACTED WITH QUARTILES OF LAGGED CGPA

Variables	(1)	(2)	(3)	(4)
	Fixed Effects		Random Effects	
Online (vs. face-to-face)	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×2nd quartile	-0.021	-0.023	0.025	0.023
	(0.022)	(0.022)	(0.022)	(0.022)
Online×3rd quartile	-0.150***	-0.153***	-0.078***	-0.081***
	(0.022)	(0.021)	(0.022)	(0.021)
Online×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 are the same as in the previous table. (2) Clustered standard errors are in parentheses. (3) ***, **, and * denote statistical significance at 1%, 5%, and 10% level of significance, respectively.

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, with the first quartile (poorest performers) as the reference group. The results are presented in Table II. 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), indicating that students below the median benefit the most. Students at the third quartile gain only about half of the bottom quartiles ($0.292 - 0.153 = 0.139$ points). The positive effect of the online format entirely disappears, leading to a null effect of the online format on performance for the top quartile.

TABLE III

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: The same as in the previous table; (2) Clustered standard errors are in parentheses; (3) ***, **, and * denote statistical significance at 1%, 5%, and 10% level of significance, respectively.

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) withdraws or takes, (4) fails a course (F grade), (5) receives a letter grade of C or better, (6) receives a letter grade of B or better, and (7) receives a letter grade of A- or better. The results are presented in Table III. The first three columns show that the students are less likely to retake a course or withdraw, which may 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 is addressed in the robustness section. Column (4) shows that students are four percentage points more likely to fail a course in online than in a 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 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 I.

5.2 AGP in Online vs. Face-to-Face Format

The FE and RE estimates of equation (2) are presented in Table IV. Hausman test statistics indicate that the FE model is preferred to the RE model. However, estimates from these models are nearly identical. The main specifications in columns (3) and (6) include time-fixed effects 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.

TABLE IV

THE EFFECT ON COURSE LEVEL AVERAGE GRADE POINTS (AGP)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
AGP	0.114***	0.102***	0.086**	0.109***	0.091**	0.083**
	(0.016)	(0.037)	(0.039)	(0.016)	(0.036)	(0.038)
CV	-0.048***	-0.028**	-0.027**	-0.046***	-0.025**	-0.026**
	(0.006)	(0.011)	(0.012)	(0.006)	(0.011)	(0.011)
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) 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, three dummy variables for 200, 300 and 400 level courses (100 level as the base category), one dummy variable for economics department (0 for BBA), two 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.

5.3 CV of Course Level 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 & Lambrinos, 2008; Fask et al., 2014; Karim et al., 2014; Diedenhofen & Much, 2017; Bilen & 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. Equation (3) examines if online instruction leads to any change in the spread of the grade distribution, and the results are presented in Table IV. Again, test statistics suggest that the FE model is preferred over the RE model. Similar to equation (2), FE and RE models also produce nearly identical estimates of the effect of online format on variation in grade points. The results show that the online format reduces the CV of course level grade points by about 0.027 points, presented in column (3) in the table. 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.

VI. ROBUSTNESS CHECK

As pointed out earlier, we do not observe students' letter grades when they retake a course (R) or withdraw from a course (W). Columns (1)–(3) in Table III show that, in online classes, the retake and withdrawal rates are significantly low. 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. In order to address this, we carry out an exercise assuming that students retake or withdraw from a course only in case of poor grades. We look at the share of students who receive a letter grade of B- or lower (about 40 per cent), a measure of poor performance. We then 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 per cent, which is about 16 per cent of the poor performers. Then, 16 per cent 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 V, which indicates that our main results in Table 1 probably underestimate the true effect. The results from the main specification presented in column (3) in Table V 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 I.

TABLE V

THE EFFECT OF ONLINE FORMAT ON STUDENT PERFORMANCE
(REPLACING Ws AND Rs)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
Online (vs. face-to-face)	0.155*** (0.008)	0.341*** (0.028)	0.264*** (0.034)	0.155*** (0.008)	0.251*** (0.026)	0.224*** (0.024)
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) The 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 per cent, which is about 16 per cent of the students receiving a grade less than B. So, 16 per cent of the Rs and Ws are randomly replaced with a letter grade of C. (2) Control variables: The same as in the previous table. (2) Clustered standard errors are in parentheses. (3) ***, **, and * denote statistical significance at 1%, 5%, and 10% level of significance, respectively.

TABLE VI

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) Control variables: The same as in the previous table; (5) Clustered standard errors are in parentheses; (6) ***, **, and * denote statistical significance at 1%, 5%, and 10% level of significance, respectively.

We conducted the same exercise for the course-instructor sample, and the results are presented in Table VI. The estimated effect of online education on AGP is positive but larger than the estimates in Table IV (0.137 vs. 0.086). However, the effect on CV (-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 are confirmed in this exercise.

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 re-estimate the effects of online education dropping the first three semesters (results are available in the appendix). 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: 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 semesters 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 show that the gains in online semesters are getting smaller over time. The effect of the second online semester is 0.121 points, while it is 0.079 in the fourth online semester. The CV of course level grade points also increases over time (negative coefficients with face-to-face as the reference group). 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 only by 0.041. These results 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 that are not controlled in this exercise.

The university started academic activities online in the middle of the Spring 2020 semester. Since Spring 2020 is a mixture of the two formats, one might object to classifying it as an online semester. So, we re-estimate models (1) to (3), dropping the observations for Spring 2020 (results are available in the appendix). For the student sample, the effect of online education (0.186) is very close to the main estimate (0.208). For the course-instructor sample, the effect of online education on AGP (0.147) is larger than the main estimate (0.086). The effect on CV is nearly identical to the main estimate (-0.028 vs. -0.027).

The results in this section confirm the 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.

VII. CONCLUSION

The COVID-19 pandemic has forced educational institutions worldwide to move academic activities online, and Bangladesh is no exception. It has created a unique opportunity to explore the effect of this technology on Bangladesh's education system. Using students' academic records from a private university in Bangladesh, we examine how online format affects student performance and if there is any systematic difference in grading. This study uses students' grades to measure performance, which may not always be directly associated with students' level of learning. We use nested panel data models to eliminate individual, time, course, and instructor-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 the use of increased group activities for assessment. Our data is not rich enough to address these issues separately in this study. We also find that instructors learn from their online experiences, which, in turn, 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, 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 windows or browser tabs’ can reduce cheating. This, however, is unlikely to stop students from using a different device or getting 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, 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.

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Appendix

Table A.1: Summary Statistics–Students' Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Whole sample			Face-to-face			Online			Difference
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	[Col(5)-Col(8)]
Grade points	68151	2.91	0.81	42831	2.88	0.83	25320	2.97	0.77	-0.09***
Withdraw	76082	0.06	0.23	49656	0.07	0.25	26426	0.03	0.18	0.03***
Retake	76082	0.05	0.22	49656	0.07	0.26	26426	0.01	0.1	0.06***
Grade: F	68151	0.01	0.08	42831	0	0.05	25320	0.01	0.11	-0.01***
Grade: C or better	68151	0.89	0.31	42831	0.88	0.33	25320	0.92	0.27	-0.04***
Grade: B or better	68151	0.6	0.49	42831	0.57	0.5	25320	0.64	0.48	-0.07***
Grade: A- or better	68151	0.24	0.43	42831	0.25	0.43	25320	0.24	0.43	0
Online	76082	0.35	0.48	49656			26426			
Female	76082	0.38	0.49	49656	0.37	0.48	26426	0.4	0.49	-0.03***
Lagged CGPA	69882	2.89	0.51	43456	2.88	0.51	26426	2.9	0.51	-0.02***
Economics Major	76082	0.13	0.34	49656	0.13	0.33	26426	0.13	0.34	-0.01**
Course level 100	76082	0.42	0.49	49656	0.51	0.5	26426	0.26	0.44	0.25***
Course level 200	76082	0.23	0.42	49656	0.23	0.42	26426	0.23	0.42	-0.01
Course level 300	76082	0.17	0.38	49656	0.15	0.36	26426	0.21	0.41	-0.06***
Course level 400	76082	0.18	0.38	49656	0.11	0.32	26426	0.29	0.46	-0.18***
Class Size	76082	38.17	6.35	49656	38.59	6.17	26426	37.37	6.62	1.22***
Age	76082	21.07	1.61	49656	20.66	1.52	26426	21.83	1.5	-1.18***
Annual income (taka)	76082	879361	4211076	49656	864945	4136246	26426	906449	4348153	-41504
Log income	76082	13.19	0.81	49656	13.18	0.81	26426	13.2	0.81	-0.02***
Merit scholarship	76082	0.02	0.15	49656	0.02	0.15	26426	0.03	0.17	-0.01***
Need-based scholarship	76082	0.06	0.24	49656	0.05	0.22	26426	0.09	0.29	-0.04***
Other Scholarship	76082	0.02	0.15	49656	0.03	0.16	26426	0.02	0.13	0.01***
Course load	76082	3.28	0.48	49656	3.25	0.45	26426	3.32	0.54	-0.07***
Course load dummy for less than 4 courses	76082	0.72	0.45	49656	0.75	0.43	26426	0.67	0.47	0.08***
GPA in SSC	76082	4.69	0.4	49656	4.69	0.39	26426	4.69	0.4	0
GPA in HSC	76082	4.39	0.51	49656	4.42	0.51	26426	4.34	0.51	0.09***
HSC to admission year gap	76082	1.18	0.66	49656	1.18	0.66	26426	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% levels of significance, respectively.

Table A.2: Summary Statistics–Course-Instructor Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Whole sample			Obs	Face-2-face		Obs	Online		Difference [Col(4)-Col(6)]
	Obs	Mean	Std. Dev.		Mean	Std. Dev.		Mean	Std. Dev.	
Average grade points	2283	2.87	0.3	1494	2.84	0.3	789	2.92	0.3	-0.08***
CV of grade points	2283	0.29	0.11	1494	0.3	0.11	789	0.26	0.11	0.03***
Online	2283	0.35	0.48	1494			789			
Female Instructor	2283	0.46	0.5	1494	0.45	0.5	789	0.48	0.5	-0.03
Instructor has a Ph.D.	2283	0.2	0.4	1494	0.21	0.41	789	0.2	0.4	0.01
Course level 100	2283	0.35	0.48	1494	0.33	0.47	789	0.38	0.49	-0.05*
Course level 200	2283	0.19	0.39	1494	0.18	0.39	789	0.2	0.4	-0.02
Course level 300	2283	0.2	0.4	1494	0.2	0.4	789	0.19	0.39	0.01
Course level 400	2283	0.27	0.44	1494	0.29	0.45	789	0.23	0.42	0.05**
BBA department	2283	0.79	0.41	1494	0.82	0.39	789	0.73	0.44	0.08***
Economics department	2283	0.21	0.41	1494	0.19	0.39	789	0.27	0.44	-0.08***
Teaching load	2283	4.06	0.83	1494	4.23	0.89	789	3.72	0.57	0.51***
Class size	2283	37.23	7.23	1494	37.66	7.25	789	36.41	7.14	1.26***
Class size: up to 30	2283	0.16	0.37	1494	0.15	0.36	789	0.19	0.39	-0.03*
Class size: 31-37	2283	0.23	0.42	1494	0.22	0.42	789	0.25	0.43	-0.03
Class size: 38-42	2283	0.38	0.49	1494	0.38	0.48	789	0.4	0.49	-0.02
Class size: 43+	2283	0.22	0.42	1494	0.25	0.43	789	0.17	0.37	0.08***

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

Table A.3: The Effect on Student's Course Level Grade Points

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	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)

(Contd. Table A.3)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
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 A.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 A.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 A.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 A.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 A.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 per cent, which is about 16 per cent of the students receiving a grade less than B. So, 16 per cent 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 A.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 per cent, which is about 16 per cent of the students receiving a grade less than B. So, 16 per cent 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, three dummy variables for 200, 300, and 400 level courses (100 level as the base category), one dummy variable for economics department (0 for BBA), two 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 A.10: The Effect on Student's Course Level Grade Points (Modified Sample)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	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)

(Contd. Table A.10)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
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 A.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, three dummy variables for 200, 300, and 400 level courses (100 level as the base category), one dummy variable for economics department (0 for BBA), two 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 A.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, three dummy variables for 200, 300, and 400 level courses (100 level as the base category), one dummy variable for economics department (0 for BBA), two 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 A.13: Modified Student Sample: The Effect on Student Performance

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	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)

(Contd. Table A.13)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			Random Effects		
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 A.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, three dummy variables for 200, 300, and 400 level courses (100 level as the base category), one dummy variable for the economics department (0 for BBA), two 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.