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▶ To cite this version:

Andrew E. Clark, Huifu Nong, Hongjia Zhu, Rong Zhu. Compensating for Academic Loss: Online Learning and Student Performance during the COVID-19 Pandemic. 2020. halshs-02901505

HAL Id: halshs-02901505

https://halshs.archives-ouvertes.fr/halshs-02901505

Preprint submitted on 17 Jul 2020

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PARIS SCHOOL OF ECONOMICS
ECOLE D'ECONOMIE DE PARIS

WORKING PAPER N° 2020 – 39

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Funded by a French government subsidy managed by the ANR under the framework of the Investissements d'avenir programme reference ANR-17-EURE-001

Compensating for Academic Loss: Online Learning and Student Performance during the COVID-19 Pandemic

Andrew E. Clark[*], Huifu Nong[†], Hongjia Zhu[‡], and Rong Zhu[§]

Abstract

The outbreak of the COVID-19 pandemic has led to widespread school shutdowns, and many schools have opted for education using online learning platforms. Using administrative data from three middle schools in China, this paper estimates the causal effects of online learning on student performance. Using the difference-in-differences approach, we show that online education improves students' academic achievement by 0.22 of a standard deviation, relative to those who stopped receiving learning support from their school during the COVID-19 lockdown. All else equal, students from a school having access to recorded online lessons delivered by external higher-quality teachers have achieved more progress in academic outcomes than those accessing lessons recorded by teachers in their own school. We find no evidence that the educational benefits of distance learning differ for rural and urban students. However, there is more progress in the academic achievement of students using a computer for online education than that of those using a smartphone. Last, low achievers benefit the most from online learning while there is no significant impact for top students. Our findings have important policy implications for educational practices when lockdown measures are implemented during a pandemic.

Keywords: COVID-19 pandemic; online learning; academic achievement.

JEL Classification Codes: H43; I21; I28.

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1 Introduction

The global outbreak of the COVID-19 pandemic has generated unprecedented public health concerns. Many countries have imposed lockdown measures to reduce social contact and to contain the spread of the Novel Coronavirus (Brodeur et al., 2020; Eyles et al., 2020). The consequent shutdowns of schools have caused challenges for teachers, students, and their parents.[1] Lost time in school can potentially generate an adverse impact on children's educational outcomes and their future well-being (Eyles et al., 2020). To mitigate the negative influence of physical closures, many schools have provided purely online lessons to their students. The evaluation of the effectiveness of distance delivery of education for students' academic outcomes is highly imperative, particularly during an ongoing severe pandemic such as the COVID-19.

This paper estimates the effects of online learning on student performance, using administrative data on ninth graders from three middle schools located in the same county within Baise City of China. During the COVID-19 lockdown, these three schools enforced different educational practices from mid-February to early April of 2020 (we call them Schools A, B and C henceforth). School A did not provide any online educational support to their students. School B used an online learning platform provided by local government, which offered a centralized portal for providing video content, communication between students and teachers, along with systems for setting, receiving, and marking student assignments. Students' online education was managed by teachers of School B. School C used the same online platform as School B during the same period, and distance education was managed by the school in the same fashion as in School B. The only exception is that, instead of using recorded online lessons prepared by own teachers in the school, School C gained access to recorded lessons delivered by teachers of the highest quality in Baise City. Starting from mid-February, students in Schools B and C spent around seven weeks on distance learning, while in the meanwhile those in School A received no learning support from their schoolteachers. After the COVID-19 restrictions were loosened, all middle schools in the county reopened on April 6. On April 7, ninth graders were notified that the local Bureau of Education scheduled an exam for each subject from April 9 to 12.

[1] According to the United Nations Educational, Scientific and Cultural Organization (UNESCO), schools in 190 countries were closed in mid-April of 2020 in response to the COVID-19 pandemic, affecting over 1.5 billion students who accounted for 90% of total enrolled learners in the world. See https://en.unesco.org/covid19/educationresponse.

Exam paper for each subject was the same for ninth graders in all the middle schools in the county.

The different educational practices of the three schools during the COVID-19 pandemic offer a natural experiment to identify the causal effects of online learning on students' academic achievement. Using the difference-in-differences (DID) approach, we show that online learning can improve student performance by 0.22 of a standard deviation, when compared with those who stopped receiving learning support from their school during the COVID-19 lockdown. Students having access to online lessons delivered by external best-available teachers have achieved a 0.06 standard deviation more increase in scholastic performance than those accessing lessons recorded by teachers in their own school. There is no evidence that the effects of online education differ for rural and urban students. However, students who used a computer as the learning device have experienced more progress in achievement than those using a smartphone. Furthermore, our quantile DID estimates suggest low-achieving students benefit the most from distance learning whilst no impact is found for top academic performers. The two online learning models of Schools B and C have both enhanced the performance of non-top students, with recorded lessons delivered by external higher-quality teachers having generated more academic benefits than those prepared by teachers in own school.

We contribute to the literature in the following ways. First, while several recent studies have discussed the effects of the COVID-19 pandemic and the consequent lockdowns on people's subjective well-being (Brodeur et al., 2020), job losses (Couch et al., 2020; Montenovo et al., 2020), social interactions (Alfaro et al., 2020), and household spending (Baker et al., 2020), there is little research assessing quantitatively their consequences for the educational sector (Eyles et al., 2020). During lockdowns, distance delivery of education is probably the only option available to mitigate the adverse influence of disrupted classroom teaching. However, there is yet any empirical evidence on the impact of online education on student performance when schools are physically shut down.[2] Does online education improve student performance during the COVID-19 crisis? If yes, which group of students can benefit the most from it? What online educational practices of schools are desirable for supporting students' academic progress? Is there any role for the government to facilitate students' remote

[2]As discussed in Eyles et al. (2020), "at least in the short run, the closure of schools is likely to impact on student achievement and the costs of putting this right are likely to be high"; "there may be some benefits too, if a switch to online education encourages greater interaction with technology and more efficient teaching practice, but these benefits are as yet unknown and unquantifiable" (page 6).

education? Shedding lights on answers to these questions, our empirical results have significant policy implications for educational practices when lockdown measures are implemented during a disastrous pandemic.

Second, this study adds to the literature on experimental evidence on the effects of instruction models on student performance (Figlio et al., 2013; Bowen et al., 2014; Alpert et al., 2016; Bettinger et al., 2017; Kozakowski, 2019). Two common features are evident in previous analyses. First, they only analyze the *relative* effects of face-to-face, fully online, and blended learning. Second, their findings were for *postsecondary* settings. An examination of *absolute* effects of instruction models necessitates a rare reference group in the data: students who have not received learning support from an educational institution within a time period but have taken the same exams as normal students in the institution. Due to the school shutdowns in China, our data include students from a middle school that received no learning support from their school for about seven weeks but took an exam immediately after returning to school when the COVID-19 restrictions were lessened. With data on them and online-learning students from two other middle schools, we provide causal evidence on the mean and distributional *absolute* effects of two different online instruction practices on the achievement of *middle school* students by using DID and quantile DID strategies.

Last, we provide new evidence on the impact of teacher quality on student achievement. Previous studies such as Rivkin et al. (2005), Araujo et al. (2016), and Jackson (2018) find that improved quality of teachers engaging in the conventional instruction model has a positive impact on student outcomes. We extend this literature by offering evidence from online education, moving beyond the conventional classroom instructions. Specifically, using DID estimations, we examine whether students in a school having access to online lessons recorded by external higher-quality teachers have more progress in scholastic performance than those in another school accessing lessons recorded by their own teachers, when all other aspects of online education were managed in the same fashion.

The remaining paper is organized as follows. Section 2 describes the background. Section 3 introduces the data. Section 4 discusses the empirical approach, and Section 5 presents the estimation results. Last, Section 6 concludes.

2 Education in three middle schools during the pandemic

Here we focus on the education in three middle schools located in the same county within Baise City of China's Guangxi Province.[3] The county has an administrative area of about 2,500 square kilometers and a population of around 370,000 people. Besides a downtown area, the county administers 12 townships composed of over 180 administrative villages. There is a total of 11 middle schools in the county, with three located in the downtown area and eight located in different townships. We have access to the administrative records of students who are ninth graders in the 2019–2020 academic year in the three middle schools located in the downtown area of the county.[4] The total number of ninth graders in these three schools is 2,025, accounting for 48.5% of all students in grade nine in the county.[5]

In China's education system, there are two semesters per year and two exams in a semester (a mid-term exam and a final exam), with several subjects tested in an exam. Governed by the local Bureau of Education, all middle schools in the county apply the same curriculum standards. There are five compulsory subjects (Chinese, Mathematics, English, Politics, and History) taught in all three years of middle school. Students only learn Geography and Biology in grades seven and eight, study Physics in grades eight and nine, and learn Chemistry only in grade nine. At the end of middle school, ninth graders need to take the city-level high school entrance exam. Scores in this exam are the most important determinant of the outcomes of ninth graders' competition for admission to good high schools within the city (Huang and Zhu, 2020).[6] For the cohort of ninth graders in our data, all middle schools in the county finished teaching all subjects in grades seven and eight and the first semester of grade nine (from September 2017 to January 2020). The second semester of grade nine, generally between February and June, was scheduled for preparing for the high school entrance exam that will normally take place at the end of June.

Due to the COVID-19 pandemic and the consequent school closures, students could not return to

[3] Per our agreement with the local government, we do not identify the county by name.

[4] These students did not need to sit an exam when finishing primary school education in June 2017. They were required to go to a middle school located within or close to their neighborhood (the proximity principle).

[5] Since 1986, China has implemented the policy of nine-year compulsory education (six years in primary school and three years in middle school). These students have been receiving compulsory education.

[6] Scores in this exam also largely determine some students' admission to vocational education schools.

their campus on the previously scheduled school starting date (February 9, 2020), although there has been no confirmed COVID-19 case in the county (up to now).[7] Here we focus on ninth graders in the three schools (Schools A, B and C) located in the downtown area of the county, which implemented different educational practices in response to the lockdown.[8]

School A: it did not make any special arrangements to support students' learning during the COVID-19 crisis. It did not require its students to study via an online platform like the other two schools. While students were told to self-study and review what was learnt in previous semesters by themselves, the school took no measure to monitor students' learning progress. The school prescribed no assignment and distributed no educational resources to students when they were locked at home.

School B: it used a flexible and centralized online learning platform provided by the Bureau of Education of Baise City, which offered a portal for providing video content, student–teacher communication, along with systems for setting, receiving, and marking assignments. It was mandatory for students to register on the online platform and to attend recorded online lessons prepared by own teachers in School B. The online classes were used to review what was learnt in previous semesters. Time slots were allocated to different subjects in the morning and afternoon in the same way as in a regular school day. Student could re-watch online lessons after class. They could ask questions and communicate online with their teachers. Moreover, teachers monitored student learning progress and participation records. There were also assignments for students to complete each week, and students' submitted works were marked and commented by teachers in School B through the learning platform.

School C: it used the same online learning platform as School B, and distance education was managed by the school in the same fashion as that in School B. The only exception is that recorded lessons available on the platform were not delivered by teachers in School C. Instead, School C gained access to recorded online lessons provided by the local government. After the COVID-19 shutdown, the Bureau of Education of Baise City organized the recordings of online classes for each subject in each grade of primary and secondary school education, and teachers selected by the government

[7]The COVID-19 cases were first reported in Wuhan, the capital city of Hubei Province at the end of 2019. On January 22 of 2020, the first infected case was confirmed in another city of Guangxi Province, which then activated a Level-I alert of public health incidents (the highest level in China) on January 24. The first confirmed COVID-19 case was reported in Baise City (but not in the county) on January 24. On February 6, the Ministry of Education of China required that all schools postpone the starting of new semester, and offline training and teaching be prohibited during the crisis.

[8]No schools in the county engaged in classroom teaching during the lockdown as it was strictly prohibited.

for fulfilling this task were of the highest quality within the city (in terms of their qualifications, teaching experience, teaching awards received, and other professional recognition).[9] However, none of the selected ninth-grade teachers were from School C. All other instructional activities online were provided by teachers in School C, the same as the arrangement in School B.

After the outbreak of the COVID-19 pandemic, both Schools B and C responded very quickly to the new mode of teaching and learning at a distance.[10] Students in these two schools started online education from mid-February of 2020, about one week after the normal starting time of a spring semester. They spent about seven weeks on distance learning, which ended on April 3. With the loosened COVID-19 restrictions, all middle schools in the county reopened on April 6. About 97.7% of ninth graders returned to school by April 7, when they were notified that the local Bureau of Education scheduled them an exam (covering contents taught in previous semesters of middle school) from April 9 to 12 (the approximate time for a midterm exam in a normal spring semester).[11] Exam paper for each subject was the same for ninth graders in all the 11 middle schools in the county.

3 Data

We have access to the administrative data on ninth graders who started middle school education in September 2017 in Schools A, B, and C. These students are in the last semester of their middle school education in the first half of 2020. Provided by the local Bureau of Education, our raw data include 2,025 ninth graders from these three schools. We have information on students' characteristics and their scores of each subject in all exams after September 2017. We focus on the exam results of the five compulsory subjects (Chinese, Math, English, Politics, and History) taught in all semesters of middle school education. Students took the first nine exams during 2017–2019. The tenth exam, the

[9]In terms of professional recognition, the education system in China ranks teachers in primary and secondary schools by levels from intern teachers (the lowest) to third class, second-class, first-class, and superior-class teachers (the highest) (Huang and Zhu, 2020).

[10]Schools B and C did not use live lessons online for two reasons. First, classroom instructions in these two middle schools have been predominantly unidimensional from teachers to students (with student-teacher communications after a class). Second, live lessons online have a higher requirement on stable and fast Internet connection than recorded lessons.

[11]As previously discussed, all middle schools in the county finished teaching all subjects in the first five semesters of middle school (from September 2017 to January 2020). The last semester (from February to June in a normal year) is used to review contents already learnt and to prepare for the high school entrance exam that normally takes place in June. Due to the COVID-19 pandemic, the time of the exam will be delayed to July 2020.

final exam of the first semester of grade nine, took place during January 6–10 of 2020, which was before the first confirmed COVID-19 case reported in Baise City on January 24. Moreover, the most recent exam (11th exam) took place during April 9–12 of 2020 after schools reopened on April 6. It is noteworthy that the exams were standardized within the county in terms of the same set of exam questions and anonymous marking process. Therefore, scores from the same exam can be used for comparison purposes across schools.

Table 1: Students' characteristics when taking the first exam in middle school

	School A		School B		School C	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Academic performance						
Total score (range: 0–560)	280.94	100.46	326.57	109.83	338.28	102.46
Chinese (range: 0–120)	67.44	19.40	78.75	19.35	81.04	16.57
Math (range: 0–120)	39.60	27.31	58.72	30.39	64.05	32.45
English (range: 0–120)	54.47	24.33	66.95	29.13	67.48	28.88
History (range: 0–100)	53.56	22.04	55.01	25.45	59.27	22.72
Politics (range: 0–100)	65.86	17.88	67.13	16.25	66.45	13.45
Student characteristics:						
Age in September 2017	13.05	0.76	12.74	0.77	12.86	0.85
Boy (yes=1)	0.44	0.50	0.47	0.50	0.42	0.49
Household head is:						
Father (yes=1)	0.63	0.48	0.71	0.45	0.77	0.42
Mother (yes=1)	0.19	0.39	0.11	0.32	0.09	0.29
Neither father nor mother (yes=1)	0.18	0.38	0.18	0.38	0.14	0.34
Home-to-school distance (kilometers)	8.78	5.53	9.87	7.13	10.52	6.96
Rural student (yes=1)	0.96	0.19	0.80	0.40	0.89	0.32
Individuals	328		871		636	

We exclude 190 ninth graders who (i) ever changed schools, (ii) missed any exam, or (iii) did not come back to school in April 2020. Our final sample consists of 20,185 observations for 1,835 students who have complete exam records in all 11 exams of five compulsory subjects. Table 1 presents the summary statistics of them when they took the first exam in middle school. Our final sample include 328 students from School A, 871 students from School B and 636 students from School C. On average, the academic performance of students in School C was the highest in the first exam, while that in School A was the lowest. The three schools share similar student age and gender compositions.

4 Identification strategy

To identify the effects of online education on student scholastic performance, we employ the following standard difference-in-differences (DID) framework:

$$Y_{ist} = Treatment_{iB} * Post_t * \beta_B + Treatment_{iC} * Post_t * \beta_C + X'_{ist}\gamma + Exam_t + \mu_i + \epsilon_{ist} \quad (1)$$

where Y_{ist} denotes the overall academic performance of student i in school s (s=A, B, C) in the tth exam (t=1,2,...,11). For ease of interpretation, we standardize total scores of the five compulsory subjects to have zero mean and unit variance.[12] $Treatment_{iB}$ is a binary variable that equals to one if student i is from School B, and $Treatment_{iC}$ is defined analogously. We consider students in School A as in the control group. $Post_t$ is a dummy variable equal to 1 if it is the 11th exam that took place in April 2020 and zero otherwise.[13] X_{ist} represents time-varying control variables including student age and class-by-school fixed effects.[14] $Exam_t$ is the exam fixed effects. μ_i denotes the individual fixed effects, which control for the differences between treatment and control groups in time-invariant observed and unobserved characteristics of students (innate ability and birth order, for example). ϵ_{ist} is the error term. We cluster standard errors at the student level to account for heteroskedasticity and any arbitrary correlations across the academic outcomes of the same student.

The validity of our DID approach is built on the assumption that the treatment and control groups would display comparable trends in academic outcomes, in the absence of different educational practices enforced by the three schools during the COVID-19 pandemic. Figure 1 shows that students in School C performed academically better than those in school B and that students in School A performed considerably worse in exams than those in the two other schools. In general, the educational outcomes of students in these three schools share very close patterns in the first ten exams in middle

[12] As a robustness check, we also have generated a measure of overall academic performance from the principal component analysis (PCA), given the high correlations in the scores of the five subjects (correlation coefficient ranges from 0.70 to 0.77 for any two of the five subjects). After applying the eigenvalue-one criterion, we retain the first component that explains about 79% of the variations in exam scores. Using the PCA index of academic performance as the dependent variable yields very close estimates to those reported in Section 5.

[13] We have not included separately $Treatment_{iB}$, $Treatment_{iC}$ and $Post_t$ in equation (1), because $Treatment_{iB}$ and $Treatment_{iC}$ have a collinearity with individual fixed effects and $Post_t$ has a collinearity with exam fixed effects.

[14] Class fixed effects and school fixed effects are not included in equation (1) because they can be perfectly predicted by class-by-school fixed effects.

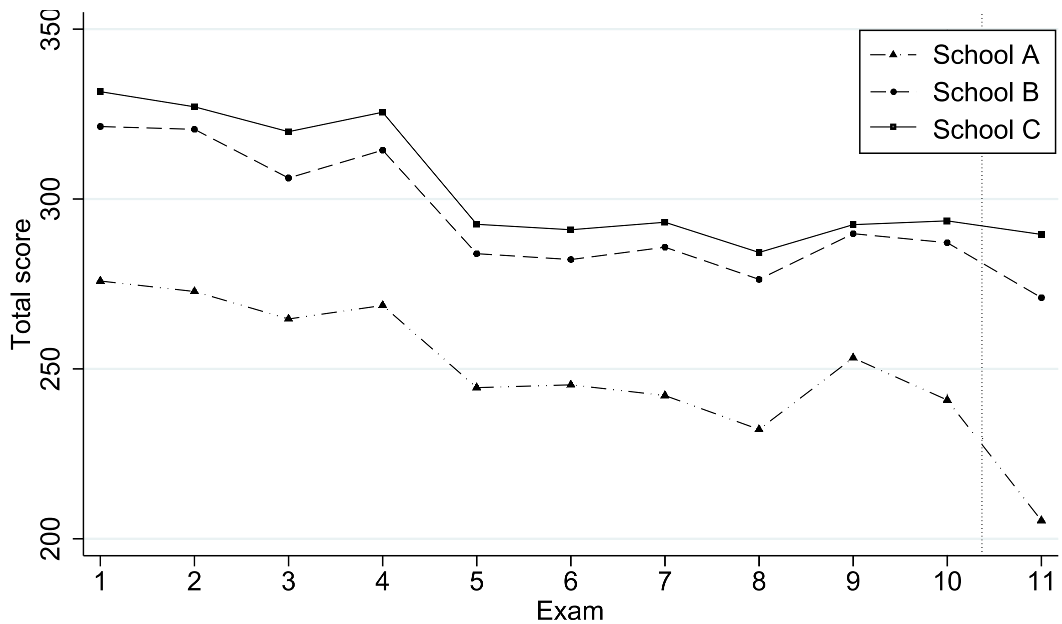

Figure 1: Parallel trends in exam scores in Schools A, B and C

school that took place before the lockdown. Therefore, the data support the parallel trends assumption.[15]

It is important to note that the students in our data come from the same county. This is ideal for identifying the causal effects of online learning on student performance as they were exposed to the same environment. If students in treatment and control groups are from different areas, then the academic effects of online education are likely to be confounded by the concurrent psychological pressures generated differently from area-specific COVID-19 conditions.

5 Results

5.1 Main results

Table 2 reports the DID estimation results. We first do not differentiate between $Treatment_{iB}$ and $Treatment_{iC}$ implemented in Schools B and C and investigate whether taking part in online learning at all (denoted by $Treatment_{iBC}$) affects student scholastic achievement. Column (i) shows that, relative to students in the control group, online learning improves the academic performance of those in the treatment group by 0.22 of a standard deviation during the pandemic.

[15] We use regression analysis as an alternative approach to verify the common trends assumption. See footnote 16.

Table 2: Main results (DID estimates)

	(i)	(ii)
$Treatment_{iBC}{*}Post_t$	0.221***	
	(0.010)	
$Treatment_{iB}{*}Post_t$		0.195***
		(0.011)
$Treatment_{iC}{*}Post_t$		0.258***
		(0.011)
Testing equality of coefficients:		
F-statistic	—	47.71
p-value	—	0.00
Individuals	1,835	1,835
Observations	20,185	20,185
Overall R^2	0.109	0.110

Notes: Dependent variable is standardized total score. Control variables include student age, class-by-school fixed effects, individual fixed effects, and exam fixed effects. Standard errors clustered at the individual level are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

We next examine whether the different online education models in Schools B and C generate differential impacts on student performance. The estimated coefficients of $Treatment_{iB}{*}Post_t$ and $Treatment_{iC}{*}Post_t$, reported in Column (ii) of Table 2, are both positive and statistically significant. The F-test rejects the null hypothesis of equality of the two estimated coefficients.[16] Therefore, online education improves student overall performance, with lessons recorded by teachers of higher quality conferring larger academic benefits, when other online educational activities were managed in the

[16] The validity of our DID estimates relies on the parallel trends assumption, which we further verify here. If our data show common trends in the scores of the ten exams in these three schools before the lockdown, then dropping randomly some of the first ten exams from our estimation sample should not change our results dramatically. However, if some exams violate parallel trends, then keeping them in the DID estimations and dropping other exams satisfying the identifying assumption are likely to generate extreme estimates that may substantially deviate from those reported in Table 2. In our empirical exercise, we drop randomly half of the first ten exams each time (a total of 252 (=C_5^{10}) different combinations), and then conduct DID estimations with reduced samples. We repeat this random process 1,000 times to increase the chance of including every possible combination of five exams and obtain the distributions of sub-sample DID estimates. The means of estimated coefficients of $Treatment_{iB}{*}Post_t$ and $Treatment_{iC}{*}Post_t$ are 0.195 (*S.E.*=0.011) and 0.256 (*S.E.*=0.016), respectively (almost identical to those in Table 2). The two distributions also exhibit limited dispersion as measured by range: the coefficient estimates of $Treatment_{iB}{*}Post_t$ range from 0.169 (*S.E.*=0.012) to 0.222 (*S.E.*=0.009), and those of $Treatment_{iC}{*}Post_t$ are between 0.218 (*S.E.*=0.016) and 0.296 (*S.E.*=0.008). As another statistical measure of variability, the interquartile ranges of the two coefficient distributions are from 0.187 (*S.E.*=0.012) to 0.203 (*S.E.*=0.012) and from 0.245 (*S.E.*=0.013) to 0.269 (*S.E.*=0.010), respectively. These narrow ranges and interquartile ranges together with Figure 1 suggest little violation of the common trends assumption. In addition, testing the null hypothesis of equality of the two coefficients in the 1,000 sub-sample regressions, the p-values obtained are all smaller than 0.004. Therefore, we reach the same main conclusions by using any five of the first ten exams as pre-treatment periods in DID estimations, lending support to the parallel trends assumption.

same way. This finding complements previous studies documenting that teacher quality impacts positively on student achievement (Rivkin et al., 2005; Araujo et al., 2016), and we extend the literature by shifting the scenario from conventional classroom instructions to online education.[17]

5.2 Heterogeneous effects of online learning by student characteristics

Our results reported in Table 2 capture the average academic effects of online learning for the overall sample. Next, we proceed to analyze the potential heterogeneous effects among students. We explore the possible differential effects across the following three dimensions of student characteristics: (i) gender (boys vs girls), (ii) type of household (from a rural household vs from an urban household), and (iii) Internet-enabled electronic device used for online learning (a computer vs a smartphone). Our difference-in-difference-in-differences (DDD) estimates are reported in Table 3.

Table 3: Heterogeneous effects of online learning by student characteristics (DDD estimates)

	(i) Gender $Group_i$=1 if boy	(ii) Type of household $Group_i$=1 if rural	(iii) Device for learning $Group_i$=1 if smartphone
$Treatment_{iB}*Post_t$	0.202***	0.191***	0.332***
	(0.014)	(0.057)	(0.028)
$Treatment_{iB}*Post_t*Group_i$	–0.017	0.005	–0.144***
	(0.021)	(0.058)	(0.030)
$Treatment_{iC}*Post_t$	0.285***	0.271***	0.398***
	(0.014)	(0.059)	(0.031)
$Treatment_{iC}*Post_t*Group_i$	–0.065***	0.014	–0.147***
	(0.022)	(0.060)	(0.033)
Individuals	1,835	1,835	1,835
Observations	20,185	20,185	20,185
Overall R^2	0.110	0.109	0.110

Notes: Dependent variable is standardized total score. Control variables include student age, class-by-school fixed effects, individual fixed effects, exam fixed effects, and all pairwise interactions among $Treatment_i$, $Post_t$ and $Group_i$. Standard errors clustered at the individual level are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

The online educational practice in School B is the most common one implemented during a lockdown, with all online instruction activities managed by teachers in this school. Column (i) of Table 3 indicates that $Treatment_{iB}$ confers close educational benefits for boys and girls. Compared

[17] We also have examined the effects of distance education on subject outcomes. Results are generally consistent with those in Table 2. We find the strongest positive impact on Politics, the weakest on Mathematics and English, with effects on Chinese and History in the middle. The differential effects are not surprising, as subject achievements generally require different skills and online learning may not impact uniformly on students' set of skills.

with School B, School C used recorded lessons designed and delivered by higher-quality teachers, with no difference in other instruction activities online. Column (i) shows that girls benefit more from $Treatment_{iC}$ than boys. In addition, Column (ii) suggests there is little difference in the academic effects of two online educational approaches between rural and urban students. Last, we examine whether the effects of distance delivery of education differ by the type of Internet-enabled electronic device available to students.[18] While Column (iii) of Table 3 suggests that both distance education models improve student performance, students having access to a computer at home have benefited more than those using a smartphone. This finding is consistent with our expectation since participating in online classes is easier and more convenient when using a computer. Consequently, the electronic device available at home matters for the effectiveness of distance education.

5.3 Heterogeneous effects of online learning along achievement distribution

The next question we ask is whether the educational effects of online learning vary with students' position in achievement distribution. We employ the unconditional quantile regression (UQR) by Firpo et al. (2009) to conduct quantile DID estimations. Key to the UQR approach is the concept of influence function in robust statistics, representing the impact of an individual observation on a distributional measure (quantile, variance, for example). Adding the influence function back to the distributional measure produces the recentered influence function. Using Y_{ist} to denote the learning outcome of student i in school s in exam t, the influence function $IF(Y_{ist},\, q_\tau)$ for the τ-th quantile of Y_{ist} is $(\tau - I(Y_{ist} \leq q_\tau))/f_{Y_{ist}}(q_\tau)$, where q_τ is the τth quantile of Y_{ist}, I is an indicator function and $f_{Y_{ist}}$ is the density of the marginal distribution of Y_{ist}. Then the recentered influence function $RIF(Y_{ist},\, q_\tau)$ can be obtained as $q_\tau + IF(Y_{ist},\, q_\tau)$. As $RIF(Y_{ist},\, q_\tau)$ is never observed in practice, we follow Firpo et al. (2009) to replace its unknown components with their sample estimators: $\widehat{RIF}(Y_{ist}, \widehat{q}_\tau) = \widehat{q}_\tau + \frac{\tau - I(Y_{ist} \leq \widehat{q}_\tau)}{\widehat{f}_{Y_{ist}}(\widehat{q}_\tau)}$, where $\widehat{q}_\tau$ is estimated as $\widehat{q}_\tau = arg\ \min\limits_{q} \sum_{i=1}^{N} (\tau - I(Y_{ist} \leq q))(Y_{ist} - q)$. The nonparametric Rosenblatt's kernel density estimator $\widehat{f}_{Y_{ist}}(\widehat{q}_\tau)$ is equal to $\frac{1}{N} \sum_{i=1}^{N} \frac{1}{h_Y} K_Y(\frac{Y_{ist} - \widehat{q}_\tau}{h_Y})$,

[18] Among the 1,835 students in our final sample, about 16% have access to a computer at home, 84% using a smartphone for remote learning. Ordinary smartphones are much more affordable than computers in China. No ninth graders in our sample reported no access to a computer or a smartphone at home. Chinese parents generally invest heavily on children's education, particularly when approaching important exams (Huang and Zhu, 2020). Unless in exceptional circumstances, ninth graders generally have supports from parents in terms of resources needed for learning purposes.

where K_Y is the Gaussian kernel and h_Y is the scalar bandwidth for Y_{ist}.

We then model $\widehat{RIF}(Y_{ist}, \widehat{q}_\tau)$ as the function of the same explanatory variables as in equation (1):

$$E[\widehat{RIF}(Y_{ist}, \widehat{q}_\tau)] = Treatment_{iB} * Post_t * \beta_{B\tau} + Treatment_{iC} * Post_t * \beta_{C\tau} + X'_{ist}\gamma_\tau + Exam_t + \mu_i. \quad (2)$$

The quantile DID estimates of $\beta_{B\tau}$ and $\beta_{C\tau}$ from equation (2) measure the causal effects of the two online education models implemented in Schools B and C on the unconditional τ-th quantile of Y_{ist} in our data.[19] We obtain standard errors clustered at the individual level via bootstrapping with 300 replications.[20] Compared with DID estimates, quantile DID estimates can provide a more adequate description of the relations between online education and the full distribution of academic outcomes.

Table 4 reports the quantile DID estimates at the 10th to the 90th percentiles of the unconditional distribution of student performance. There is strong evidence that the effects of online education are heterogeneous along achievement distribution. The estimated coefficients of $Treatment_{iB} * Post_t$ and $Treatment_{iC} * Post_t$ at the bottom end of distribution are generally larger than those at the top end. For example, the positive academic impact of online education carried out in School B at the 20th percentile is over three times as large as its impact at the 80th percentile. Low performers are thus most positively impacted by online learning programs. Another interesting finding is that top academic performers at the 90th percentile are not affected by distance delivery of education. A possible explanation is that highly capable students can identify the best approach for improving their performance regardless which teaching practice is employed by their school during the lockdown. Therefore, except for top academic performers, the two online instructional models implemented in Schools B and C have both enhanced student performance. Furthermore, while Table 2 indicates that the average impact of $Treatment_{iC}$ is greater than that of $Treatment_{iB}$, Table 4 suggests that it is mainly driven by the larger effects of $Treatment_{iC}$ for low achievers at the 10th and 20th percentiles. From the 30th to the 80th percentile of the exam-score distribution, although the estimated coefficients of $Treatment_{iC} * Post_t$ appear to be consistently larger than those of $Treatment_{iB} * Post_t$, the differences

[19] Examples of applications of the UQR method in a quantile DID setting include Havnes and Mogstad (2015), Herbst (2017) and Baker et al. (2019) that evaluate universal child care programs in Norway, the US, and Canada, respectively.

[20] Borgen (2016) extends the UQR approach to include high-dimensional fixed effects and clustered standard errors.

Table 4: Heterogeneous effects of online learning along student achievement distribution (Quantile DID estimates)

	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
$Treatment_{iB}*Post_t$	0.319***	0.371***	0.316***	0.214***	0.191***	0.188**	0.155***	0.106*	–0.059
	(0.079)	(0.062)	(0.055)	(0.058)	(0.057)	(0.076)	(0.063)	(0.057)	(0.047)
$Treatment_{iC}*Post_t$	0.486***	0.452***	0.354***	0.263***	0.227***	0.247***	0.192***	0.160***	0.045
	(0.076)	(0.063)	(0.055)	(0.061)	(0.059)	(0.077)	(0.060)	(0.054)	(0.046)
Testing equality of coefficients:									
F-statistic	16.16	4.73	1.02	1.92	0.52	2.33	0.83	1.60	8.69
p-value	0.00	0.03	0.31	0.17	0.47	0.13	0.36	0.21	0.00
Individuals	1,835	1,835	1,835	1,835	1,835	1,835	1,835	1,835	1,835
Observations	20,185	20,185	20,185	20,185	20,185	20,185	20,185	20,185	20,185
Overall R^2	0.033	0.092	0.074	0.048	0.026	0.031	0.006	0.000	0.000

Notes: Dependent variable is the recentered influence function of the τth quantile of standardized total score. Control variables include student age, class-by-school fixed effects, individual fixed effects, and exam fixed effects. Bootstrapped standard errors clustered at the individual level are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

are not significant at conventional statistical levels.

6 Conclusion

Many schools have switched from classroom teaching to education using online platforms in response to the outbreak of the COVID-19 pandemic. In this paper, we analyze the causal effects of online learning on student academic performance using administrative data from three middle schools in China, which implemented different educational practices for about seven weeks during the COVID-19 lockdown. Using the DID approach, we show that online learning has a positive impact on students' educational performance, when compared with those who stopped receiving learning support from their school. All else equal, online lessons recorded by higher-quality teachers confer additional academic benefits. The academic benefits of online learning are found to not differ for rural and urban students. However, students who used a computer as the remote learning device have achieved more academic progress than those using a smartphone. Furthermore, our quantile DID estimates suggest academically weaker students have benefited the most from online education, while the educational outcomes of top academic performers have not been affected.

Our findings have important policy implications for educational practices when lockdown measures are imposed during a severe pandemic like the COVID-19. First, when physically shut down, schools should create distance learning resources for students given the beneficial influence of online education. Also, since low-ability students are the biggest beneficiaries, distance delivery of education can help narrow the achievement gap between them and their higher-achieving peers in school. Second, the quality of teachers who design and deliver recorded online lessons has a positive impact on students' academic performance. Local government can organize top-quality teachers to prepare online lessons complying with local curriculum standards and then make them available to schools and students. This is a cost-effective endeavor that has great potential to generate substantial economies of scale, since each school does not have to prepare its own version of online classes that may not yield the optimal educational benefits. Last, government should ensure all students have the resources necessary to access online education, potentially through joint efforts with the telecommunications sector. If resources available are constrained, priority should be given to low-achieving children as they benefit the most from distance learning. Since students with access to a computer as the online learning device can benefit more than those using a smartphone, government can play a more active role in providing or subsidizing investment in computers for students having no access to one at home.

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