Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Does school shutdown increase inequality in academic performance? Evidence from COVID-19 pandemic in China

Haoye Liao, Sen Ma, Hao Xue

Institute for Economic and Social Research, Jinan University, Guangzhou, China
Freeman Spogli Institute for International Studies, Stanford University, Stanford, USA

ARTICLE INFO

JEL classification:
I21
I24

Keywords:
COVID-19
School Shutdown
Educational Inequality
Academic Performance

ABSTRACT

The school shutdown due to the global pandemic of coronavirus disease 2019 (COVID-19) can lead to an increase in educational inequality through disproportionately affecting disadvantaged children. We use data from a unique survey of 7202 junior high school students and their parents from Shaanxi province to explore whether the school shutdown enlarged the educational gap between students with different parental socioeconomic statuses (SES) during the pandemic. We find that students with more highly educated parents experienced an increase in relative test rankings after the shutdown period. A 1-year increase in parents’ education led to a relative 0.18-percentile increase in students’ rankings of total test scores. We also identify the mechanisms behind the enlarged gap by means of heterogeneity analyses. We show that parents’ education mainly affected children’s academic performance through parents’ engagement in their children’s homeschooling, mitigating the negative impacts of Internet addiction on students, and serving as substitutes for teachers who were unable to teach well online.

1. Introduction

Beginning in early 2020, COVID-19 brought the world into a public health crisis. Schools across the globe were forced to shut down, and classrooms were shifted to online delivery during the lockdown period. The unanticipated school closure may have enlarged the gap in academic achievement by disproportionately affecting disadvantaged children (UNICEF, 2020; van de Werfhorst, 2021). For example, online education required access to the Internet and related facilities, which not all families could afford. Likewise, the school shutdown shifted the burden of supervision from teachers to parents, whose ability to support their children’s learning was and remains related to their socioeconomic status (SES).

In this study, we combine administrative data on a sample of 7202 Grade 7 students’ test scores before and after the school shutdown with online survey data on students’ family backgrounds collected from Shaanxi Province in China to investigate how the COVID-19 school shutdown may have enlarged educational inequality. Specifically, we estimate the changes in relative test rankings before and after the school shutdown by students’ family socioeconomic status. We measure family socioeconomic status by parents’ educational attainment. Then, we use a two-way fixed effects model to estimate the differentiated effects of school shutdown on the changes in students’ relative academic rankings by parental years of schooling, taking advantage of the fact that parents’ educational attainment.

* We thank the financial support from 111 project of China (No. B18026), and Shaanxi Primary Education National Teaching Achievement Incubation Project (No. SCGFH63).
* Corresponding author.
E-mail addresses: liaohaoye@outlook.com (H. Liao), senma2@jnu.edu.cn (S. Ma), haoxue@stanford.edu (H. Xue).

https://doi.org/10.1016/j.chieco.2022.101847
Received 23 January 2022; Received in revised form 11 June 2022; Accepted 18 July 2022
Available online 1 August 2022
1043-951X/© 2022 Elsevier Inc. All rights reserved.
attainment is predetermined and not affected by children’s current academic performance.

We find that after the 8-week school shutdown period, parental socioeconomic status was an important factor in enlarging students’ educational gap. In the empirical design, we use school-level students’ percentile rankings of test scores to measure their relative performance because the absolute test scores were not entirely comparable across schools. Then, we compare the changes in students’ percentile rankings of test scores before and after the COVID-19 period by parental years of schooling and find the following results. First, students with more highly educated parents experienced an increase in relative test rankings after the shutdown period. In terms of magnitude, a 1-year increase in parents’ education led to a relative 0.18-percentile increase in rankings of total scores (equivalently, 0.33 points in total raw scores). In other words, the predicted gap between students with parents who graduated from college and those with parents who only graduated from primary school increased by nearly 2 percentiles in total rankings (equivalently, 3 points in total raw scores) after the school shutdown. Second, paternal education rather than maternal education played a key role during the school shutdown, which complements Alon (2020)’s findings that more fathers participated in childcare activities during the homeschooling period than before. Third, the effects were driven mostly by the changes in math and English scores, while the gap in Chinese scores was insignificantly enlarged. This result is intuitive since math and English subjects require additional analytical skills and expertise compared with the Chinese subject, making parents’ education crucial in determining how effectively parents can assist their children during the homeschooling period. Finally, boys were more sensitive to their parents’ socioeconomic status than girls, and disadvantaged boys from less educated families are more likely to be disproportionately affected, which in turn enlarges the gender gap in academic performance following the school shutdown.

Our empirical design assumes that the gap between students with better family backgrounds (higher parents’ education) and those with worse family backgrounds would stay unchanged in the absence of the school shutdown. We cannot directly test this assumption using our current sample because our sample students were still in primary school before the academic year affected by the pandemic, and thus, test score data are not available. As an alternative strategy, we use the student-level data from China Education Panel Survey (CEPS) from 2013 to 2015, which contains information on test scores and family background for Chinese junior high school students, to conduct a placebo test. We utilize a sample of students from CEPS who are also junior high school, Grade 7 students. Then, we track the changes in relative test rankings across two periods of similar length to the main analysis, before the COVID-19 school shutdown. We use the same model specification and estimate the changes in the gap by parents’ education before the COVID-19 school shutdown.

Next, we utilize the rich information on the characteristics of students, parents, and teachers to explore the mechanisms through which parental socioeconomic status affected students’ relative academic performance. First, we find that both parents’ education and income could help students improve percentile rankings during the homeschooling period, but these improvements resulted as a function of different mechanisms. Parents’ education affected students’ performance independently from parents’ income when parents could directly accompany or supervise students during the school shutdown period. On the other hand, the significance of parents’ income arose only if parents were absent from students’ homeschooling. Second, we find that parents’ education affected students’ performance through mitigating the negative influences of Internet overuse or addiction. The parents’ education effect was more significant among students who were relatively more addicted to the Internet. Third, parents served as potential substitutes for teachers when teachers were less professional and less able to teach online courses well. We find that the parents’ education effect was statistically and economically significant only if the corresponding teachers’ education levels or intrinsic abilities were lower than the median level in our sample.

Our study contributes to the literature on the impact of the COVID-19 school shutdown on education, especially educational inequality (Andrew et al., 2020; Stelitano et al., 2020; Donnelly & Patrinos, 2021; Panagouli et al., 2021; Spitzer & Musslick, 2021). From the theoretical perspective, Azevedo, Hasan, Goldberg, Geven, and Iqbal (2021) and Agostinelli, Doepke, Sorenti, and Zilibotti (2022) argue that school closures can influence the function of the great equalizer from multiple perspectives because online education is not a perfect substitute. From the empirical perspective, several studies have to date documented the enlargement of educational inequality after the school showdown. Grewenig, Lergetporer, Werner, Woessmann, and Zierow (2021) find that learning time is reduced more for low-achieving students than high-achieving students. Maldonado and De Witte (2021), Engzell, Frey, and Verhagen (2021) and Contini, Di Tommaso, Muratori, Piazzalunga, and Schiavon (2021) find that parents’ (or mothers’) education level increases the educational gap during the pandemic. Zhang (2021) finds evidence of a greater level of gender inequality attributed to the school shutdown. Our study contributes to previous literature by clarifying the mechanisms through which parental characteristics increase the educational gap, taking advantage of the rich information we acquire from student-level surveys. We show that parents’ education mainly affects children’s academic performance through parents’ engagement in their children’s homeschooling, mitigating the negative impacts of Internet addiction on students and serving as substitutes for teachers when teachers are less professional and relatively ineffective in the delivery of online schooling. Specifically, to our best knowledge, we are the first study to provide empirical evidence suggesting that parents partially substitute for teachers in providing educational inputs during the homeschooling period, which echoes the theoretical hypothesis proposed by Agostinelli et al. (2022). In addition, we also provide evidence from a developing country, where more disadvantaged children may be negatively affected by the school shutdown, to

\footnote{Apart from the enlarged educational inequality, researchers are also concerned about the absolute learning loss of schooling-age children during the COVID-19 school shutdown. Kuhfeld et al. (2020), Tomaski, Helbling, and Moser (2021), Engzell et al. (2021), and Maldonado and De Witte (2021) find that students suffered significant learning losses during the pandemic lockdown. However, despite that the majority of students performed worse, Clark et al. (2021) shows that online education assistance helps withstand the negative impact of the school shutdown and reduces inequality.}
Researchers across various disciplines have proposed a wide range of evidence for the positive correlation between parents’ socioeconomic status and children’s academic achievement (Cameron & Heckman, 2001; Chevalier, 2004; Heineck & Riphahn, 2009; Chevalier, Harmon, O’Sullivan, & Walker, 2013; Azomahou & Yitbarek, 2016). Compared with existing studies, we focus on the short-run intergenerational impacts of parental socioeconomic status in the course of a public health crisis. We find that parents’ education not only increases intergenerational mobility in the long run but also enhances students’ ability to resist short-run shocks.

Meanwhile, this article contributes to the assessment of the performance of K-12 students receiving online courses by different family socioeconomic status. In previous literature, researchers mainly adopted the randomized control trial method to investigate the effectiveness and efficiency of online teaching courses (Alpert, Couch, & Harmon, 2016; Bettinger, Fox, Loeb, & Taylor, 2017; Bowen, Chingos, Lack, & Nygren, 2014; Figlio, Rush, & Yin, 2013) and suggested that online courses are a complement to traditional classes, but not a perfect substitute. Researchers have also assessed the equality of online education and have expressed concerns about the inequality of distance learning (Emanuel, 2013; Hansen & Reich, 2015). The COVID-19 school shutdown can be viewed as a quasi-experiment in which students with different socioeconomic statuses are forced to receive online courses. The results of this study reveal that parents’ educational attainment is a predictor of the level of inequality in students’ achievement in online courses because online courses require greater engagement by parents in the learning process.

The remainder of the article is organized as follows: the second section introduces the background on the school shutdown in Shaanxi Province and the overall COVID-19 policy in China; the third section describes the data used in the analysis; the fourth section introduces the empirical method; the fifth section presents the results, and the final section concludes.

2. Background

The sudden outbreak of the Coronavirus Disease 2019 (COVID-19) epidemic in Wuhan, China at the beginning of 2020 brought a dramatic shock to China’s economy and education system. When this novel disease broke out in early 2020, students had returned to their homes and were on winter vacation. In the face of the sudden interruption, the Ministry of Education (MOE) first announced a delay in the school opening date of the spring semester on January 27, 2020 and then issued a “Disrupted Classes, Undisrupted Learning” (Ting Ke Bu Ting Xue) notice on February 12, 2020, which required hundreds of millions of primary and secondary school students to continue their studies at home to protect them from contracting the disease. The guideline was then implemented by provincial-level governments in a decentralized way: provincial governments made their own plans on how to conduct online education and when to reopen the schools.

Like most provinces in China other than Hubei, Shaanxi province was not severely affected by the COVID-19 pandemic epidemiologically. The cumulative number of confirmed infected cases was 308, with only three deaths as of May 20, 2020 (National Health Commission of the People’s Republic of China, 2020). As of our survey in December 2020, the number of new cases due to the local transmission had been zero for months, since February 12, 2020. Despite the low number of confirmed cases, Shaanxi province consistently followed the Chinese central government’s guidelines and implemented strict lockdown policies to contain the virus.

The timeline of the school shutdown policy in Shaanxi province is presented in Fig. 1. First, the Spring Festival holiday was extended such that students would not return to school, and parents would not go back to work. On February 10, while the daily new confirmed infection cases were falling steadily, the Shaanxi government decided to reopen the economy and gradually allow people to return to work (Ma, Sun, & Xue, 2020). At the same time, students started their new semester with online schooling. However, the local government was very cautious in its decision to reopen schools physically. It was not until April 13, nearly two months after eliminating local transmission of the disease, that schools were reopened. Other provinces in China also reopened their schools on a similar timeline and adjusted according to local COVID-19 situations (Clark, Nong, Zhu, & Zhu, 2021; Li et al., 2021).

Realizing that online learning may not be a perfect substitute for face-to-face teaching, many provinces, including Shaanxi, had made plans to readjust the school calendar to make up for instruction lost during this period. For example, Shandong Province provided that the total time for instruction would remain unchanged so the exact number of days missed from the original school opening date would be made up out of some of the weekend days in the spring semester and parts of the summer vacation (World Bank, 2020).

Plans for the school shutdown induced a growing concern about how it might affect disadvantaged students. The government’s
The overall approach to dealing with the equality concern of school shutdown was mainly through the promotion of equal and universal access to online learning rather than targeting disadvantaged students uniquely (EdTechHub, 2020). Both the central and local governments made huge efforts to increase access to remote education, seeking to reach as many students as possible through televised and online lessons. However, there has been no systematic evaluation as to whether these efforts successfully reached targeted students on the ground.

---

**Fig. 1.** The timeline of school shutdown in Shaanxi province.  
*Notes:* This figure shows the timeline of the school shutdown policy in Shaanxi and the timing of the three exams we study. First, the Spring Festival holiday was extended such that students would not return to school, and parents would not go back to work. On February 10th, students started their new semester with online schooling. Schools were reopened on April 13th and the midterm exam was launched at the same time. Around July 2020, the final exam was held. In December 2020, we conducted an online survey to collect information on students’ characteristics and family backgrounds.
3. Data

We combine administrative data on students’ test scores before and after the shutdown with online survey data on students’ characteristics and family background to study the differentiated effects of school shutdown by their parents’ socioeconomic status. Our sample consists of 7202 Grade 7 (during lockdown) junior high school students (Grade 8 during our survey), sampled from 98 schools in Shaanxi Province during the 2019–2020 academic year. We followed four steps in selecting our sample. First, the Provincial Bureau of Education provided a full list of 328 junior high schools across all ten prefectures in Shaanxi. Second, we selected schools from the list according to a predetermined sampling standard, which was designed to study English learning in Shaanxi province. As a result, 144 out of the 328 schools met the standard and were all included in our sample. Third, 23 schools dropped out of the surveys due to an unwillingness to participate or some logistic reasons. Finally, each school selected two classes taught by different English teachers to participate in the survey. All students from the two classes were included in the sample. In total, 121 schools completed the survey or submitted the administrative test score data. To generate a final sample with complete information for analysis, we dropped 23 out of 121 schools due to the incompleteness of their data. Of the 23 schools, 7 schools were dropped because they provided data only on Grade 7 (during the survey) students who were in primary school during the COVID-19 lockdown. 14 of the remaining 114 schools were dropped because they did not submit test scores data. Moreover, we dropped additional two schools that submitted test score data without completing the survey. The final sample submitted for analysis consisted of 7202 students from 98 schools.

Since this selection process was not entirely randomized, a potential concern was how representative our sample would be. We make the best use of the data we have and conduct several balance tests to address the representativeness of our sample. First, unfortunately, we only have the school names for the 144 out of the 328 schools that met the first selection standard. For the rest of the schools that did not meet the standard, we do not have any information to conduct meaningful tests. Therefore, our sample best represents schools enrolled in our English learning program rather than all junior high schools from Shaanxi province. Second, we provide a balance test of schools’ characteristics between schools enrolled (121 schools) and schools that dropped out due to willingness to participate in our survey program (23 schools) in Table A1. The table suggests that the 23 schools that chose not to enroll in our program were from regions that are relatively farther away from the prefecture center and relatively poorer in terms of 2019 GDP levels. Therefore, our study may underrepresent schools from relatively less developed regions. Third, among enrolled schools, we also test the balances between the final sample (98 schools) and the sample that are excluded from our final sample due to data incompleteness (23 schools; shown in Table A2). The result indicates that our selection of the final sample from enrolled schools does not incur any serve bias. Finally, we provide a balance test of English teachers’ characteristics between English teachers who participated in the survey program and those who did not. The results shown in Table A3 suggest little evidence supporting the systematic difference in characteristics between enrolled and non-enrolled teachers. Fig. 2 shows the geographic distribution of the 98 schools in our final sample. Even with some degree of selection, we still manage to find sampled schools in all prefectures of Shaanxi Province. Thus, our study provides a more representative sample than previous studies conducted in China about the effects of COVID, which tend to rely on information from several schools in a certain county (Clark et al., 2021).

The test score data were reported by each sampled school according to the administrative records. We collected test scores on three subjects—Chinese, math, and English—before and after the pandemic. Specifically, we collected test scores on three exams: the final exam of the first semester of the 2019–2020 academic year (before the COVID-19 lockdown around January 2020, referred to as Exam (1)), the midterm exam of the second semester of the 2019–2020 academic year (After COVID-19, around April–May 2020, referred to as Exam (2)) and the final exam of the second semester of 2019–2020 academic year (After COVID-19, around July 2020, referred to as Exam (3)). The detailed timeline of the exams is also presented in Fig. 1.

Two potential concerns arise when we try to compare students’ exam performance across schools and across different periods. First, the exams were designed by each school independently and were, therefore, not standardized, which made it difficult to compare students’ performance across different schools. Second, within a school, the degree of exam difficulty varied over different exams. We cannot exclude the possibility that schools adjusted the exam difficulty (probably to a lower degree) after the school shutdown to make overall learning loss seem lower in terms of test scores. To tackle the first concern, we study the within-student changes in test scores by controlling for student fixed effects in all analyses. As shown in Table A4, the within-student comparison suggests that students experienced a significant learning loss after the school shutdown in terms of the changes in raw test scores. To tackle the second concern—that exam difficulty may not be comparable across time—our analysis, therefore, focuses on changes in students’ relative performance by examining the changes in students’ percentile rankings within the school level instead of the changes in absolute raw scores. Given this nature, we believe our data are best suited to study relative performance or educational inequality rather than absolute learning loss during the school shutdown period.

In December 2020, we conducted an online survey to collect basic information about students and their parents. Teachers of sampled classes sent a link to the survey to students and parents via group chats and required them to finish the survey within a certain period of time. In the survey, we collected students’ basic information, including age, gender, whether the student is boarding at school, which family member supervises students’ learning, and students’ self-efficacy measured by General Self-Efficacy Scale (GSE; Jerusalem & Schwarzer, 1992) as well as parents’ information containing age, education level, job types, working location, and long-term monthly income. The summary statistics of students’ and parents’ characteristics are shown in Table 1. The summary statistics of

---

7 The project was originally aimed to study students’ English learning in junior high schools in Shaanxi province. To get enough students and English teachers in our sample, we set our selection criteria as (a) at least two classes per grade and (b) at least one English teacher per grade.

8 We acquired English teachers’ characteristics from their school administrations even though their students did not participate in the program.
Empirical strategy

This section presents the empirical models used to estimate the differentiated effects of the school shutdown on changes in students’ test rankings by parents’ socioeconomic status. We employ a two-way fixed effects model specified as Eq. (1) to compare the changes in test rankings in pre-and post-COVID-19 periods among students with different parents’ socioeconomic statuses. Specifically, we use parents’ education level (years of schooling) to measure parents’ socioeconomic status. To capture the differentiated effects of school shutdown on changes in relative test rankings among students with different parents’ education, we interact parents’ years of education with the time dummy variable indicating “after COVID-19.” Hence, the coefficient on the interaction term indicates the differences in the changes in test rankings between students with higher SES parents and students with lower SES parents. We expect the coefficient of the interaction term to be positive because students of parents with greater amounts of schooling are expected to suffer less from the school shutdown in terms of changes in relative test ranking compared with students whose parents have lesser amounts of schooling.

\[ Y_{it} = \beta_1 \text{Educ}_i \times \text{COVID}_t + \beta_2 \text{COVID}_t + \mu_i + \epsilon_{it}. \] (1)

In Eq. (1), \( Y_{it} \) is the learning outcome for the \( i \)-th student in the \( t \)-th period (exam). Because we are not certain whether the standard used in the tests before and after the COVID-19 school shutdown was comparable for all schools, we mainly focus on the analysis of students’ performance relative to their peers within the same school. We adopt three different measures of learning outcomes to capture the performance of students relative to their peers. First, we generate each student’s percentile ranking for each exam at the school level. Second, we use each student’s absolute ranking for each exam at the school level. Third, we standardize test scores to a standard normal distribution with zero mean and one standard deviation at the school and exam levels. Among the three measures of students’ performance, we focus on the changes in percentile ranking as our main results because the effect on the standardized score is difficult to interpret, and the absolute ranking measure is affected by the total number of students participating in the exams. We treat the other two measures as robustness analysis and show that the parental effects on the three measures are similar. Moreover, \( \text{Educ}_i \) is the self-reported years of schooling of parents; \( \text{COVID}_t \) is a dummy variable indicating “after the outbreak of COVID-19,” and \( \beta_1 \) captures the changes in the gap in relative test rankings among students with different parents’ education levels. \( \beta_2 \) captures the changes in test rankings of students with uneducated parents (zero years of education). \( \mu_i \) are student fixed effects, and \( \text{COVID}_t \) serves as the control of time fixed effects since it is colinear with the exam fixed effects. We cluster the standard errors at the student level.

The critical assumption for estimation in this study is that the gap in students’ test rankings with different family backgrounds would not change significantly without the COVID-19 school shutdown. We cannot directly test this assumption because students were still in primary school before the academic year affected by the pandemic, and thus, test score data are unavailable. As an alternative strategy, we use the survey data from CEPS from 2013 to 2015, which contains information on test scores and family background for students.

---

9 To be precise, we standardize the test scores by schools using the formula: \((x_i - \bar{x}_j)/sd(x_j)\), where \(x_i\) is the test scores of \(i\)-th student and \(\bar{x}_j\) and \(sd(x_j)\) are the sample average and standard deviation of test scores of \(j\)-th school.
Table 1
Summary Statistics.

|                          | (1)      | (2)      |
|--------------------------|----------|----------|
|                          | Mean     | S.D.     |
| **Students’ Characteristics** |          |          |
| Gender (1 = Male)        | 0.492    | 0.500    |
| Hukou (1 = Rural)        | 0.674    | 0.469    |
| No. of Siblings          | 0.930    | 0.767    |
| **Mother’s Characteristics** |          |          |
| Age                      | 39.902   | 4.707    |
| Income (Monthly, RMB)    | 2667.090 | 3342.136 |
| Income (Monthly, log)    | 6.146    | 3.328    |
| Years of Education       | 9.829    | 3.961    |
| Unemployed during Lockdown (1 = Yes) | 0.598    | 0.490    |
| Worked at Home during Lockdown (1 = Yes) | 0.265    | 0.441    |
| Went out for Work during Lockdown (1 = Yes) | 0.137    | 0.344    |
| **Father’s Characteristics** |          |          |
| Age                      | 42.279   | 4.928    |
| Income (Monthly, RMB)    | 4697.987 | 4290.623 |
| Income (Monthly, log)    | 8.062    | 1.413    |
| Years of Education       | 10.278   | 3.666    |
| Unemployed during Lockdown (1 = Yes) | 0.471    | 0.499    |
| Worked at Home during Lockdown (1 = Yes) | 0.299    | 0.458    |
| Went out for Work during Lockdown (1 = Yes) | 0.230    | 0.421    |
| **Average Parent’s Characteristics** |          |          |
| Age                      | 41.091   | 4.585    |
| Income (Monthly, RMB)    | 3682.538 | 3285.960 |
| Income (Monthly, log)    | 7.901    | 1.070    |
| Years of Education       | 10.053   | 3.494    |
| **Number of Observations (Students):** | 7202 |          |

Notes: This table summarizes the demographic characteristics of students and parents. The “Unemployment” measure includes all individuals who are temporarily not working during the pandemic lockdown. It does not indicate that the workers are losing their contracts.

Table 2
Summary of Students’ Tests Scores.

|                          | (1)      | (2)      |
|--------------------------|----------|----------|
|                          | Mean     | S.D.     |
| **Final Exam before Lockdown, Exam (1)** |          |          |
| Raw Total Scores         | 222.111  | 55.296   |
| Total Percentiles        | 49.422   | 28.054   |
| Total Rankings           | 49.056   | 34.808   |
| Standardized Total Scores| 0.021    | 0.985    |
| **Midterm Exam after Lockdown, Exam (2)** |          |          |
| Raw Total Scores         | 213.740  | 56.659   |
| Total Percentiles        | 49.428   | 28.061   |
| Total Rankings           | 49.056   | 34.759   |
| Standardized Total Scores| 0.023    | 0.985    |
| **Final Exam after Lockdown, Exam (3)** |          |          |
| Raw Total Scores         | 219.517  | 55.586   |
| Total Percentiles        | 50.042   | 28.092   |
| Total Rankings           | 50.079   | 36.201   |
| Standardized Total Scores| 0.030    | 0.985    |
| **Number of Observations (Students):** | 7202 |          |

Notes: This table summarizes the information of students’ total test scores in the three exams.
Chinese junior high school students, to test the validity of this assumption.

5. Empirical results

5.1. The effects of parental socioeconomic status

Table 3 shows that the school shutdown enlarged the gap in students’ relative test rankings by their parents’ education levels after the school shutdown. First, Table 3 uses the average parents’ years of schooling as the explanatory variables, and columns (1)–(3) present the estimates using three different measures of students’ relative learning outcomes: the total scores’ percentile rankings, absolute rankings, and standardized scores, respectively. We find that the school shutdown significantly enlarged the gap between students with different parents’ educational attainment regardless of which measures we use. In terms of magnitude, a 1-year increase in parents’ schooling was associated with a relative 0.18-percentile increase in student ranking after COVID-19 (equivalent to 0.33 points increase in total raw scores). We plot the predicted changes in relative percentile test rankings by parents’ education level in Fig. 3. Fig. 3 (a) shows that the predicted drop in relative rankings of students with uneducated parents after COVID-19 was 1.49 percentiles. On the other hand, moving the student’s parental years of education from 0 to 8.3 could have eliminated the drop, which means that students with parents who at least completed their junior-high education would have experienced increases in their relative rankings after the school shutdown. Moreover, the predicted gap between students with parents who graduated from college and those with parents who only graduated from primary school increased by 2 percentiles in total scores (equivalently, about 3 points in raw scores) after the school shutdown. Therefore, the learning gap was enlarged between students with different levels of parents’ education after the COVID-19 school shutdown.

Table 3 also shows that paternal education rather than maternal education played a key role during the school shutdown, as seen in columns (4)–(6), which give estimates of the changes in the gap between students with different paternal and maternal years of education. Compared to the overall effects, paternal education rather than maternal education revealed statistically and economically significant impact. Specifically, a 1-year increase in students’ fathers’ education would lead to a relative 0.2 percentile increase in total rankings (equivalent to 0.38 points in raw scores). For students’ mothers’ education, however, the effect was neither statistically nor economically significant. One potential explanation for the significant impact of paternal education is that during the COVID-19 lockdown, more fathers participated in childcare activities, including helping their children study, compared to the pre-COVID period (Ma, Sun, & Xue, 2020; Alon, 2020). Therefore, the importance of fathers’ education in the context of the lockdown increased, but that of mothers had no significant change.

The discrepancy in academic performance after the school shutdown was mainly driven by the changes in math and English performance. Table 4 shows the estimates of parents’ education on children’s post-COVID performance by different subjects (Chinese, math, and English) that are the three basic courses that all primary and junior-high students are obligated to take in China. The results indicate that the gaps in math and English were significantly enlarged between students with different levels of parents’ education, while the gap in Chinese was not. Intuitively, when the burdens were shifted from teachers to parents during the lockdown, children demanded more assistance from parents. Compared with the Chinese subject, the math and English subjects require more analytical skills and expertise. Therefore, parents’ education levels played a more important role in determining how well they could help their children in math and English studies.

We also find that the gender gap was enlarged during the school shutdown, driven by the higher relative drops in test rankings among disadvantaged boys with lower parents’ SES. We estimate the effects of parents’ education on male and female students separately in Table 5. Columns (1) and (2) show the effect of parents’ education on males and females respectively. Then, we also plot the predicted changes in percentile test rankings by parents’ education for male students and female students separately in Fig. 3 (b). We find that the effects of parents’ education on both genders were statistically significant, although the effect was slightly larger for boys than for girls. In terms of magnitude, our results suggest interestingly that the decrease in percentile ranking for boys was substantially larger than for girls when their parents are uneducated (2.36 percentiles for boys, 0.57 percentiles for girls). The percentile ranking of boys increased if their parents’ education level is greater than 12 years (i.e., senior high school graduates). In contrast, it only required 4 years of education for parents (i.e., primary school drop-outs) for girls to increase their percentile ranking. This finding indicates that disadvantaged boys from less educated families were more likely to be disproportionately affected as a result of the school shutdown. These findings complement those of Zhang (2021), who also finds that girls suffered less than boys in terms of the level of test scores loss after the school shutdown using a sample of college students. In addition, we also investigate the overall change in the gender gap in terms of relative academic performance (relative percentile ranking) in column (3). The negative estimates strongly suggest that the gender gap was significantly increased following the school shutdown since boys initially performed worse than girls before the school shutdown (not shown in the table). As also suggested by Fig. 3 (b), this enlarged gender gap is predicted to diminish as parents’ education increases. One potential explanation for this is that boys demanded more external support and supervision in their daily learning activities than did girls, which were burdened by parents during the school shutdown. Therefore, the importance of parents’ own characteristics increased.

5.2. Placebo analysis

The critical identification assumption of the research design is that the gap between students with different family backgrounds would not change significantly in a non-COVID period. As mentioned in Section 4, due to data limitations, we indirectly test the assumption by using a sample of Grade 7 students from the China Education Panel Survey (CEPS) from 2013 to 2015. The main idea of
The Differentiated Effects of School Shutdown on Students’ Test Rankings by Parents’ Educational Attainment.

|                        | Average Parent | Mother or Father |
|------------------------|----------------|------------------|
|                        | (1)            | (2)              | (3) | (4) | (5) | (6) |
| Parents’ Edu*COVID      | 0.180***       | 0.238***         | 0.00592*** | 0.197** | 0.231*** | 0.00689** |
|                         | (0.0624)       | (0.0648)         | (0.00222) | (0.0788) | (0.0800) | (0.00285) |
| Father’s Edu*COVID      |               |                  |        | −0.00783 | 0.0175 | −0.000628 |
|                         |               |                  |        | (0.0715) | (0.0721) | (0.00259) |
| Mother’s Edu*COVID      | −1.494**       | −1.884***        | −0.537** | −1.635** | −2.030*** | −0.589** |
|                         | (0.656)        | (0.661)          | (0.0235) | (0.666) | (0.672) | (0.0238) |
| COVID                   | −0.0537**      |                  |        |          |        |        |
|                         | (0.0715)       |                  |        |          |        |        |
| Student FE              | Y              | Y                | Y      | Y         | Y         | Y      |
| No. of Tests            | 7202           | 7202             | 7202   | 7202      | 7202      | 7202   |

Notes: This table shows the estimation results of the differentiated effects of school shutdown on students’ test rankings by parents’ educational attainment. Columns (1) to (3) show the effects of the average education level of mother and father using percentile rankings, absolute rankings, and standardized scores as the dependent variables respectively; columns (4) to (6) show separately the effects of maternal and paternal education using percentile rankings, absolute rankings, and standardized scores as the dependent variables respectively.

All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.

this test is to use a representative sample of Grade 7 students who are not affected by the pandemic as a placebo test. There are a few advantages of using the CEPS dataset. First, the CEPS is a national survey conducted before the outbreak of COVID-19 and covers a wide range of regions, including Shaanxi. Second, the CEPS data include a similarly large number of Grade 7 students as ours and have rich information on family background. We use the same model specification to estimate the variation in the gap in test rankings by parents’ educational attainment. We track the changes in test rankings across two periods which are similar in length to our main specification before the onset of the pandemic. The placebo estimates are presented in Table 6. We find no statistically significant result, and the magnitudes are also much smaller than the main specifications. Hence, we provide this placebo analysis as evidence to support the validity of the identification assumption. Nevertheless, there could still be some systematic differences between the CEPS sample and the sample in this study, which is a limitation of our research design.

Moreover, we also conduct a technical placebo test to further check the effect of unobserved student characteristics on the estimates we obtain. Following Chetty, Looney, and Kroft (2009) and Li, Lu, and Wang (2016), we randomly assign parents’ education to our sample and generate false parents’ education status for each student. If the random process produces an estimate close to zero, then our results are not sensitive to the unobserved characteristics. Otherwise, our results could be biased. By replicating the random generating process 1000 times, the distribution of these placebo estimates is presented in Fig. A1. Fig. A1 shows that the placebo estimates are centered around zero and that the entire distribution is far from the estimate we have in column (1) of Table 3 (0.18). Therefore, our results under this technical placebo test are solid.

5.3. Mechanisms

In addition to the main results, we further discuss the reasons behind the wider gap. We consider the mechanisms from three perspectives: parents’ income and presence at home, students’ level of addiction to the Internet, and teachers’ characteristics.

5.3.1. Parents’ income and presence

There are two channels through which parents’ education level can affect children’s performance. First, parents’ education is associated with family income. Wealthier families could invest more resources into children’s education during the pandemic to prevent the decrease in education quality attributable to online teaching (Bacher-Hicks, Goodman, & Mulhern, 2021; Emanuel, 2013; Hansen & Reich, 2015). Second, parents are likely to spend more time staying with their children during the lockdown. As a result, parents who are more highly educated than others can improve the quality of homeschooling for their children (Brom et al., 2020; Brossard et al., 2020; Gimenez-Nadal & Molina, 2013; Kumar, Kroon, & Laloo, 2014; Panaoura, 2020).

To examine the two potential channels proposed above, we horse race parents’ education and parents’ income (in logarithm) within the same regression, which reveals that both of these factors mattered. As shown in column (1) of Table 7, both parents’ education and income effects were statistically significantly positive, which indicates that both factors could help children improve percentile ranking during the school shutdown. Specifically, the size of the parents’ education effect was similar to the size of the
parents’ income effect. This is because one standard deviation of parents’ education amounts to nearly a one-third standard deviation of (log) parents’ income (shown in Table 1), and the one-third unit of the parents’ income effect is comparable to the one unit of the parent’s education effect.

To further clarify how parents’ education and income affected the gap in performance, we estimate the heterogeneous impacts of

Fig. 3. Predicted Effects of Parents’ education on Percentile Test Rankings.

Notes: This figure shows the predicted changes in students’ percentile test rankings after the school shutdown period (vertical axis) by parents’ years of education (horizontal axis). Figure (a) shows the effect on all students. Figure (b) shows separately the effects on male and female students.
### Table 4
The Differentiated Effects of School Shutdown on Students’ Test Rankings by Parents’ Educational Attainment (Different Subjects).

|                      | (1)       | (2)       | (3)       |
|----------------------|-----------|-----------|-----------|
|                      | Chinese   | Math      | English   |
| Parents’ Educ*COVID  | 0.112     | 0.160***  | 0.256***  |
|                      | (0.081)   | (0.075)   | (0.071)   |
| COVID                | −0.840    | −1.257    | −2.226*** |
|                      | (0.851)   | (0.784)   | (0.753)   |
| Student FE           | Y         | Y         | Y         |
| No. of Tests         | 3         | 3         | 3         |
| No. of Students      | 7202      | 7202      | 7202      |

Notes: This table shows the estimation results of the differentiated effects of school shutdown on students’ test rankings by parents’ educational attainment and three different subjects. The percentile ranking in test scores is used as the dependent variable. Columns (1) to (3) show the estimates of aggregate effects of both mother and father on Chinese, Math, and English percentiles respectively. All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.

### Table 5
The Differentiated Effects of School Shutdown on Students’ Test Rankings by Parents’ Educational Attainment and Students’ Gender.

|                      | (1)       | (2)       | (3)       |
|----------------------|-----------|-----------|-----------|
|                      | Male      | Female    | Full Sample |
| Parents’ Educ*COVID  | 0.201**   | 0.151*    | 0.176***   |
|                      | (0.088)   | (0.089)   | (0.062)   |
| Male*COVID           |           |           | −1.289***  |
|                      |           |           | (0.432)   |
| COVID                | −2.361**  | −0.572    | 0.826     |
|                      | (0.929)   | (0.930)   | (0.691)   |
| Student FE           | Y         | Y         | Y         |
| No. of Tests         | 3         | 3         | 3         |
| No. of Students      | 3541      | 3661      | 7202      |

Notes: This table shows the estimation results of the differentiated effects of school shutdown on students’ test rankings by parents’ educational attainment and students’ gender. The percentile ranking in total test scores is used as the dependent variable. Columns (1) and (2) show the estimates of aggregate effects of both mother and father on male and female students’ relative performance respectively. Column (3) shows the estimate of the absolute change in the gender gap in the second row using the full sample. All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.

### Table 6
The Effects of Parents’ education on the Changes in Students’ Test Rankings Using the CEPS Sample (Before the Pandemic).

|                      | Average Parent | Mother or Father |
|----------------------|----------------|-----------------|
|                      | (1) Percentiles | (2) Rankings | (3) Standardized Scores | (4) Percentiles | (5) Rankings | (6) Standardized Scores |
| Parents’ Educ*Post   | 0.041           | 0.001           | −0.002 |
|                      | (0.063)         | (0.062)         | (0.002) |
| Father’s Educ*Post   |                | 0.112           | 0.107     | 0.001 |
|                      |                | (0.077)         | (0.076)   | (0.003) |
| Mother’s Educ*Post   | −2.322***       | −1.769***       | 0.012     | −2.483*** | −1.956*** | 0.008 |
|                      | (0.674)         | (0.671)         | (0.023)   | (0.686)   | (0.677)   | (0.024)  |
| Post                 |                |                |           |           |           |           |
| Student FE           | Y               | Y               | Y         | Y         | Y         | Y         |
| No. of Tests         | 2               | 2               | 2         | 2         | 2         | 2         |
| No. of Students      | 7349            | 7349            | 7349      | 7349      | 7349      | 7349      |

Notes: This table shows the estimation results of parents’ education effect on the changes in students’ total test ranking using CEPS sample as a placebo test. Columns (1) to (3) show the estimates of aggregate effects of both mother and father using percentile rankings, absolute rankings, and standardized scores as the dependent variables respectively; columns (4) to (6) show the maternal and paternal education effects using percentile rankings, absolute rankings, and standardized scores as the dependent variables respectively. All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.
school shutdown on different subgroups of students by parents’ presence and engagement in students’ study during the pandemic. We create three variables to measure parents’ engagement in students’ study at home: parents working at home while being the main supervisor of students’ learning (defined as Work at Home), parents staying at home (unemployed or working at home) while being the main supervisor of students’ learning (defined as Stay at Home), and the student receiving supervision from any family member at home with parents being the main supervisor of students’ learning (defined as Supervise). Then, we estimate the heterogeneous effects of parents’ education by whether parents engaged in students’ learning or not during the pandemic.

First, we find strong evidence suggesting that the underlying reason for the enlarged gap due to parents’ education during the pandemic was parents’ engagement in children’s studies. Table 7 shows that the parents’ education effects were only statistically significant within the subgroup of students who were accompanied and supervised by their parents under the three different measures of parental engagement. For instance, as can be seen in columns (2)–(7), the parents’ education effect among students accompanied and supervised by at least one of the parents during the pandemic was statistically significant. In contrast, the estimates of the parents’ education effect among students not accompanied by their parents were statistically insignificant. This finding indicates that the effects of parents’ education on children’s academic performance were conditional on parents’ company and supervision during the pandemic. Therefore, the effects of parents’ educational attainment on children’s academic performance during the school shutdown stemmed from the increase in parental company and supervision.

Second, there is also evidence showing that the importance of parents’ income arose when parents couldn’t accompany their children during the school shutdown. As columns (3), (5), and (7) of Table 7 show, the parents’ education effects were statistically insignificant when parents were absent in the homeschooling period. The parents’ income effect, however, was significant among students who were not supervised by their parents. This finding indicates that when parents were absent in children’s homeschooling period, more monetary investments became crucially effective for children to overcome weaknesses in online schooling. Therefore, we conclude that parents’ education and income work differently through two opposite channels (parents’ presence and absence).

5.3.2. Students’ internet addiction levels

Students are exposed more frequently to electronic devices than ever before during the school shutdown as a result of the need for distance learning. Therefore, one potential concern is that students are more likely to overuse the Internet and form Internet-addiction-related behavior (Singh, Singh, Singh, Jangid, & Gupta, 2020; Grevenig et al., 2021; Servidio, Bartolo, Palermiti, & Costabile, 2021a, 2021b) and parents’ education would affect children’s academic outcomes through mitigating the negative effects of Internet-addiction-related behavior.

Table 7
Heterogeneous Parents’ education Effects by Parents’ Presence and Engagement in Students’ Studies.

|                      | Full Sample | Work at Home | Stay at Home | Supervise |
|----------------------|-------------|--------------|--------------|-----------|
|                      | (1)         | (2)          | (3)          | (4)       |
| All                  | Yes         | No           | Yes          | No        |
| Parents’ Educ*COVID  | 0.140**     | 0.283**      | 0.078        | 0.027**   |
| (0.066)              | (0.130)     | (0.081)      | (0.087)      | (0.105)   |
| Parents’ Income*COVID| 0.349*      | -0.543       | 0.541**      | -0.026    |
| (0.207)              | (0.485)     | (0.229)      | (0.293)      | (0.269)   |
| COVID                | -3.855**    | 1.964        | -4.861***    | -1.500    |
| (1.553)              | (3.739)     | (1.732)      | (2.222)      | (2.011)   |
| Student FE           | Y           | Y            | Y            | Y         |
| No. of Tests         | 3           | 3            | 3            | 3         |
| No. of Students      | 7202        | 2178         | 5024         | 5030      |

Notes: This table shows the heterogeneous effects of parents’ education by parents’ presence and engagement in students’ studies during the pandemic. Students’ percentile ranking in test scores is used as the dependent variable. Column (1) shows the effects of both parents’ education and income using the full sample. We use three variables to measure parents’ engagement in students’ studies during the pandemic: Work at Home, Stay at Home, and Supervise. Work at Home equals one (zero otherwise) if parents were working at home while being the main supervisor of students’ learning, Stay at Home equals one (zero otherwise) if parents were staying at home while being the main supervisor of students’ learning, and Supervise equals one (zero otherwise) if the student received supervision from any family member at home while parents being the main supervisor of students’ learning. Columns (2) to (7) show the heterogeneous effects by the three variables respectively. All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.

10 The “Work at Home” and “Stay at Home” variables are created by combining the answers to two questions: parents’ working status during the pandemic and whether parents are normally the main supervisor of students’ learning. The “Supervise” variable is created by combining the answers to two questions: whether the students was supervised by any family members during the pandemic and whether parents are normally the main supervisor of students’ learning.
We examine the student’s Internet addiction channel by comparing the heterogeneous impacts of parents’ education on two different subgroups of students (higher and lower levels of Internet addiction). The level of Internet addiction is measured by the scores on seven questions asking students about their attitudes toward the usage of the Internet during the pandemic.\textsuperscript{11} We, therefore, construct three indices measuring the Internet addiction level. The first index is simply to take the equally weighted average scores over the seven questions. The second index is to take the weighted average scores over the seven questions, with weighting specified as each question’s standard deviation\textsuperscript{12}; the more the score of a question deviates, the higher the weight it would acquire. The third index is constructed by using the principal component analysis approach (PCA), which refines the variations of the scores of the seven questions and uses the most important common components to measure the level of Internet addiction. We define students with higher Internet addiction levels if the three indices are above the median levels among all students.

First, we find strong evidence suggesting that parents’ education affected students’ performance by mitigating the negative impacts of Internet overuse or addiction. From columns (1)–(3) of Table 8, we can see that the gap was significantly enlarged among students with higher levels of Internet addiction, while the enlarged gap was statistically and economically insignificant among students with lower levels of Internet addiction. Moreover, the drop in relative test rankings of disadvantaged students was also substantially larger among students with higher levels of Internet addiction than among students with lower levels. In other words, parents’ education positively affected students’ performance only if the students were relatively more addicted to the Internet, which negatively affected students’ test scores since they spend less time on their studies. When the students are more affected by the Internet, the importance of their parent’s education rises because more highly educated parents could provide more help to their children to mitigate the negative impacts of Internet addiction.

Second, we find that boys suffered more from Internet addiction than girls during the school shutdown. Beyond the investigation of the heterogeneity among the full sample of students, we also explore the heterogeneity among male and female students, which are shown in columns (4)–(6) and columns (7)–(9) of Table 8 respectively. Similar to the full sample estimation, the gap was significantly enlarged only if the students were more addicted to the Internet regardless of their gender. However, we find that disadvantaged boys witnessed a substantially larger relative drop in test rankings than disadvantaged girls if they were more addicted to the Internet. For boys with Internet addiction, if their parents are uneducated, the predicted drop in percentile ranking was around 4 percentiles. In contrast, the predicted drop for girls with uneducated parents and Internet addiction was less than 1 percentile and statistically insignificant. Also, it took over 10 years of increase in parents’ education to eliminate the drop in relative percentile rankings among boys, while this figure ranged from 3 to 6 among girls, provided that they are more addicted to the Internet. This finding suggests that the negative impacts of the Internet were more stubborn among boys than among girls since it took more effort from parents to mitigate the negative effects. Boys, therefore, were relatively more negatively affected by Internet addiction than girls. The larger gender gap we discuss in Section 5.1 could be partially explained by the fact that boys suffered disproportionately more from Internet addiction than girls and that boys also demanded more support and help from their parents to mitigate the effects during the school shutdown.

### 5.3.3. Teachers’ characteristics

An understudied question when considering potential factors affecting students’ academic outcomes during a school shutdown is the impact of teachers’ characteristics. When classrooms are shifted online during the school shutdown, teachers’ teaching activities are disrupted to a larger extent if they are not well-adapted to teaching online and fail to handle the issues in the virtual classroom (Abid, Zahid, Shahid, & Bukhari, 2021; Alolaywi, 2021; Collazos, Pozzi, & Romagnoli, 2021; Cutri, Mena, & Whiting, 2020; Mukhtar, Javed, Arooj, & Sethi, 2020; Sepulveda-Escobar & Morrison, 2020). Therefore, it is possible that parents’ impact arises only if parents serve as substitutes for teachers due to the ineffectiveness of online teaching.

We examine the effects of teachers’ characteristics by analyzing the heterogeneity of parents’ education effect by students’ English teachers’ characteristics. Since we only have data on the characteristics of English teachers, we focus on the impact on English test scores.\textsuperscript{13} We define disadvantaged teachers’ characteristics using four measures: teachers above middle age, teachers with less experience in teaching, teachers with lower educational attainment, and teachers with lower intrinsic ability. First, teachers’ ages are crucial for students’ online learning experience. Some pedagogical studies suggest that older teachers would be less confident in teaching using computers or other similar devices since they are not sufficiently knowledgeable about these technologies compared to their younger colleagues (Jones, 2004; Teo, 2008; Yaghi, 2001). We, therefore, define disadvantaged teachers’ ages by the cut-off of

---

\textsuperscript{11} The seven self-efficacy questions are as follow, scoring 1 to 5 where 1 = never and 5 = very often. 1. I hope the time use on the Internet could be increased to fulfill my desire. 2. My actual time use on the Internet exceeds my expectations. 3. I want to stop surfing the Internet, but I can’t control myself. 4. Because of my overuse of the Internet, I had forgotten to finish my homework, been reluctant to do my homework, or skipped classes. 5. I don’t tell my teachers or parents about how I use the Internet. 6. I have had a conflict with my parents or other guardians because of the way I use the Internet. 7. I think the Internet helps me get rid of difficulties, depression, or helplessness.

\textsuperscript{12} Specifically, let $w_j$ denote the weight given to the $j$-th question ($j = 1, 2, \ldots, 7$), then $w_j = \frac{\sigma_j}{\sum \sigma_j}$ where $\sigma_j$ stands for the standard deviation of the $j$-th question, and the weighted index equals $\sum_{j=1}^{7} w_j \times score_{ij}$. We argue that the question would contain more information if its standard deviation is higher, and, therefore, a higher weight should be given to it to make the index more informative.

\textsuperscript{13} Since we only have the survey data of the corresponding English teachers available, we discuss the characteristics of these English teachers in this study. As discussed in Section 5.1, most of the variation of enlarged gap is driven by the changes in English scores, which makes the investigation of English teachers’ characteristics representative enough to reveal the impacts of teachers on students’ performance during the school shutdown. However, without discussing the roles of teachers of the other two subjects makes our conclusion limited to some extent, which is also a limitation of our study.
middle age (45 years of age). Second, teaching experience is also important when considering teachers’ influence. Experienced teachers receive more on-the-job training and have more experience in managing the classroom and dealing with students concerns than novice teachers (Meskill, Mossop, DiAngelo, & Pasquale, 2002; Harris & Sass, 2011; Dolighan & Owen, 2021).

We define less experienced teachers by whether the teachers’ years of teaching are below the median level in our sample. Third, teachers’ years of education measure teachers’ professionalism and the training they have received. We measure less educated teachers by whether the teachers’ years of education are below the median level in our sample. Finally, we consider the effect of unobserved teachers’ intrinsic ability on students’ online learning. We construct an index measuring teachers’ ability by obtaining the residuals of the earnings function proposed by Mincer (1975).14 We define lower-ability teachers if the index is below the median level in our sample.

We find little evidence indicating that the rise in the effect of parents’ education was due to teachers’ disadvantaged ages or experience. First, from column (1) of Table 9, we find that the effect of parents’ education was statistically significant for both subgroups of students regardless of their teacher’s age, even though the magnitude of the parents’ education effect was larger among students whose teachers were above 45 years of age than among students whose teachers were younger. We then statistically test this difference in magnitude in the seventh row (Chow, 1960; Toyoda, 1974), which revealed that this difference was statistically insignificant at any level. From column (2) of Table 9, we find a similar pattern for the heterogeneous effects by teacher’s experience. Combining these two results, we conclude that parents’ characteristics affected students’ post-COVID academic outcomes through channels other than teachers’ ages or experience.

In contrast, we find strong evidence suggesting that the effect of parents’ education arose only if teachers were less educated or had lower intrinsic ability, which might reduce the quality of online teaching. From column (3) of Table 9, we can see that the parents’ education effect was statistically and economically significant among students whose teachers’ educational attainments were below

---

14 According to the earnings function (Mincer, 1975), a representative teacher’s earnings is determined by Eq. (2).

\[ Earnings_i = \beta_0 + \beta_1 Edu_i + \beta_2 Experience_i + \beta_3 Experience_i^2 + x_i \delta + \epsilon_i \tag{2} \]

Where the dependent variable is \( i \)-th teacher’s average monthly earnings (log), \( Edu_i \) is the years of education of \( i \)-th teacher, \( Experience_i \) is the years of teaching of \( i \)-th teacher, \( x_i \) is a vector of covariates including type of contract (formal or informal) and the school dummies (to eliminate wage variation across schools), and \( \epsilon_i \) is the error term. As pointed out by Griliches (1977), the most prominent unobserved characteristics in the Mincer function is the intrinsic ability, which is absorbed by the error term. The most of the proportion of error term of Eq. (2), therefore, captures the teachers’ ability. We follow this framework and use the residuals (a consistent estimate of the error term) as a measure of the teachers’ unobservable intrinsic ability.
Finally, we also find that parents’ education by English teachers effects were below the median. In contrast, the effect was statistically and economically insignificant among students with better family backgrounds. These findings indicate that parents served as substitutes for teachers when teachers were less professional and not able to teach well. While disadvantaged students learn less from less competent teachers, students with better family backgrounds could receive support from parents to mitigate this loss during the school shutdown.

### 6. Conclusion

Using unique survey data collected in Shaanxi province of China, we examine the differentiated short-run effects of the COVID-19-related school shutdown on Grade 7 students by their parents’ educational attainments. We take advantage of the fact that Shaanxi province imposed similar public health measures, including school shutdown, as did other provinces outside Hubei in early 2020, although the severity of COVID-19 transmission was low in Shaanxi. Treating the school shutdown as an exogenous shock and comparing students’ test rankings before and after the school shutdown by their parents’ SES (measured by parents’ education level), we find that a 1-year increase in parents’ years of schooling accounted for about a 0.18-percentile increase in total test rankings after the school shutdown.

In addition to the main findings, we further shed light on the mechanisms behind the enlarged gap by heterogeneity analyses. First, we find that parents’ engagement in students’ homeschooling was the underlying contributor to the wider gap in test scores, while the importance of parents’ income arose only when parents were absent. Second, we find that parents’ education levels affected students’ relative performance by mitigating the negative impacts of the overuse of Internet. Finally, we also find that parents’ educational inputs served as substitutes for teachers’ during the school shutdown if teachers were less professional or less able to teach well online.

Although this paper only investigates the short-run effects of the COVID-19 school shutdown empirically, it provides a piece of novel evidence of interest to policymakers that the short-run school shutdown, which protects students from contracting the disease, could result in a wider gap in learning outcomes between students with different family backgrounds. These short-run effects might be persistent and long-lasting and ultimately lead to lower intergenerational educational mobility. So far, we recommend that policymakers should take these potential social costs of a wider gap in students’ learning outcomes into account when designing school shutdown measures for epidemic control.

### Table 9

Heterogeneous Parents’ education Effects by Teachers’ Characteristics.

| Definition of Disadvantage | Middle-Aged | Less Experienced | Less Educated | Lower Ability |
|---------------------------|-------------|------------------|--------------|--------------|
|                           | Age above 45| Years of Teaching below Median = 15 | Years of Education below Median = 15.69 | Teacher Ability Index below Median = –0.001 |
| Panel A: Estimation of students with disadvantaged teachers’ characteristics, | | | | |
| Parents’ Educ*COVID       | 0.295***    | 0.153           | 0.778***     | 0.402***     |
| (0.113)                   | (0.0969)    | (0.182)         | (0.105)      |
| COVID                     | –3.543***   | –0.819          | –7.219***    | –3.810***    |
| (1.232)                   | (1.049)     | (1.829)         | (1.102)      |
| No. of Students           | 2954        | 1851            | 1329         | 2977         |
| Panel B: Estimation of students with advantaged teachers’ characteristics | | | |
| Parents’ Educ*COVID       | 0.151**     | 0.204**         | 0.0789       | 0.0110       |
| (0.0733)                  | (0.0813)    | (0.0662)        | (0.0755)     |
| COVID                     | –0.901      | –2.026**        | –0.554       | 0.276        |
| (0.765)                   | (0.834)     | (0.705)         | (0.793)      |
| No. of Students           | 4248        | 5351            | 5873         | 4225         |
| Group A-Group B Chow Test | 0.145       | –0.051          | 0.699***     | 0.391***     |
| (0.135)                   | (0.126)     | (0.193)         | (0.129)      |
| Student FE                | Y           | Y               | Y            | Y            |
| No. of Tests              | 3           | 3               | 3            | 3            |

Notes: This table shows the heterogeneous effects of parents’ education by English teachers’ characteristics. Students’ percentile ranking in test scores is used as the dependent variable. We use four variables to measure teachers’ characteristics: teachers’ ages, experiences, years of schooling, and intrinsic abilities. The results are shown in columns (1) to (4) respectively. Panel A presents the estimation for students with disadvantaged teachers’ characteristics. Panel B presents the estimation for students with advantaged teachers’ characteristics. All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.
**Appendix A**

**Table A1**
Testing the differences in characteristics of schools by program enrollment.

|                      | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------|-----|-----|-----|-----|-----|-----|
|                      | N   | Non-Enrolled (SD) | N   | Enrolled (SD) | Difference (SE) | p-values |
| Urban (1 = urban school) | 23  | 0.957 (0.209) | 121 | 0.942 (0.234) | 0.014 (0.048) | 0.768 |
| Distance to County Center (km) | 23  | 10.222 (13.38) | 121 | 8.048 (9.836) | 2.175 (2.930) | 0.464 |
| Distance to Prefecture Center (km) | 23  | 68.968 (38.817) | 121 | 45.568 (43.254) | 23.401 (8.999) | 0.014 |
| log County GDP 2019 | 23  | 14.060 (0.533) | 121 | 14.719 (0.969) | -0.659*** (0.142) | 0.000 |
| log County Population 2019 | 23  | 3.357 (0.422) | 121 | 3.656 (0.567) | -0.300*** (0.102) | 0.006 |
| log County Per Capita GDP 2019 | 23  | 1.493 (0.476) | 121 | 1.853 (0.619) | -0.360*** (0.114) | 0.003 |

**Notes:** This table shows the balance test of schools’ characteristics by whether the school participated in the survey program or not. Column (6) shows the p-values of the difference of each characteristic. Significance level: *p < .10; **p < .05; ***p < .01.

**Table A2**
Testing the differences in characteristics of enrolled schools by data completeness.

|                      | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------|-----|-----|-----|-----|-----|-----|
|                      | N   | Excluded (SD) | N   | Included (SD) | Difference (SE) | p-values |
| Urban (1 = urban school) | 23  | 0.913 (0.288) | 98  | 0.949 (0.221) | -0.036 (0.064) | 0.579 |
| Distance to County Center (km) | 23  | 5.586 (6.612) | 98  | 8.626 (10.393) | -3.040* (1.733) | 0.085 |
| Distance to Prefecture Center (km) | 23  | 51.828 (54.932) | 98  | 44.098 (40.233) | 7.729 (12.154) | 0.530 |
| log County GDP 2019 | 23  | 14.697 (1.082) | 98  | 14.724 (0.946) | 0.027 (0.245) | 0.913 |
| log County Population 2019 | 23  | 3.665 (0.650) | 98  | 3.654 (0.550) | 0.011 (0.147) | 0.940 |
| log County Per Capita GDP 2019 | 23  | 1.822 (0.655) | 98  | 1.860 (0.613) | -0.038(0.150) | 0.801 |

**Notes:** This table shows the balance test of enrolled schools’ characteristics by whether the school is included or excluded in our final sample in the analysis. An enrolled school would be dropped from the sample if it did not contain any Grade-8 (during the survey) students, or if it did not submit either survey or test scores data. Column (6) shows the p-values of the difference of each characteristic. Significance level: *p < .10; **p < .05; ***p < .01.

**Table A3**
Testing the differences in characteristics of english teachers by program participation.

|                      | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------|-----|-----|-----|-----|-----|-----|
|                      | N   | Non-Participants Mean (SD) | N   | Participants Mean (SD) | Difference (SE) | p-values |
| Gender (1 = male) | 592 | 0.123 (0.329) | 304 | 0.128 (0.335) | -0.005 (0.023) | 0.832 |
| Local (1 = local) | 592 | 0.725 (0.447) | 304 | 0.701 (0.459) | 0.024 (0.032) | 0.455 |
| Hukou (1 = rural) | 592 | 0.166 (0.372) | 304 | 0.191 (0.394) | -0.025 (0.027) | 0.355 |
| Years of Education | 581 | 15.652 (1.542) | 298 | 15.611 (1.434) | 0.042 (0.105) | 0.692 |
| Years of Teaching | 592 | 14.509 (7.903) | 304 | 14.046 (7.472) | 0.463 (0.538) | 0.390 |
| Age | 592 | 37.591 (6.853) | 304 | 37.227 (6.742) | 0.364 (0.478) | 0.447 |
| Professional Title (0 = lowest, 5 = highest) | 582 | 2.497 (0.936) | 300 | 2.420 (0.909) | 0.077 (0.065) | 0.241 |
| Teacher Ability Index | 573 | -0.004 (0.274) | 295 | 0.007 (0.231) | -0.011 (0.018) | 0.543 |
| Formal Contract (1 = formal) | 592 | 0.836 (0.683) | 304 | 0.872 (0.742) | -0.036 (0.147) | 1.047 |

(continued on next page)
Table A3 (continued)

|                     | (1)         | (2)          | (3)          | (4)          | (5)          | (6)          |
|---------------------|-------------|--------------|--------------|--------------|--------------|--------------|
|                     | N           | Non-Participants Mean (SD) | N           | Participants Mean (SD) | Difference (SE) | p-values     |
| Monthly Earnings    | 592         | 4927.573 (0.370) | 304         | 4823.553 (0.335) | 104.02      | 0.328        |
|                     |             | (1628.008)  |              | (1439.953)   |              |              |
| log Monthly Earnings| 592         | 8.447 (0.373)  | 304         | 8.442 (0.292)  | 0.004       | 0.850        |

Notes: This table shows the balance test of English teachers’ characteristics by whether their students participated in the survey program or not (We acquire English teachers’ basic information from school administration even though their students did not participate the program). Column (6) shows the p-values of the difference of each characteristic. Significance level: *p < .10; **p < .05; ***p < .01.

Table A4
Comparison of raw test scores before and after the school shutdown.

|                     | (1)         | (2)          | (3)          | (4)          |
|---------------------|-------------|--------------|--------------|--------------|
|                     | Total       | Chinese      | Math         | English      |
| Exam (2)            | –8.371***   | –0.944***    | –4.758***    | –2.669***    |
|                     | (0.410)     | (0.162)      | (0.232)      | (0.185)      |
| Exam (3)            | –2.595***   | 0.0776       | 0.0562       | –2.729***    |
|                     | (0.385)     | (0.156)      | (0.206)      | (0.183)      |
| Student FE          | Y           | Y            | Y            | Y            |
| No. of Tests        | 3           | 3            | 3            | 3            |
| No. of Students     | 7202        | 7202         | 7202         | 7202         |

Notes: This table shows the estimation results of the changes in students’ raw test scores in the two post-lockdown exams. The raw test scores are used as the dependent variables. Columns (1) to (4) show the estimates of changes in total, Chinese, Math, and English scores respectively. All robust standard errors in parentheses are clustered at the student level. Significance level: *p < .10; **p < .05; ***p < .01.

Fig. A1. Placebo effect of parents’ education on students’ academic performance during the pandemic.

Notes: This figure shows the distribution of placebo estimates of parents’ education effect using the falsely generated parents’ education level. Each estimate is obtained by exercising our main model specification given that the parents’ education is randomly assigned to each student, and we replicate this process 1000 times.

References

Abid, T., Zahid, G., Shahid, N., & Bukhari, M. (2021). Online Teaching Experience during the COVID-19 in Pakistan: Pedagogy–Technology Balance and Student Engagement. Fudan Journal of the Humanities and Social Sciences, 14(3), 367–391.
Agostinelli, F., Doepke, M., Sorrenti, G., & Zilibotti, F. (2022). When the great equalizer shuts down: Schools, peers, and parents in pandemic times. Journal of Public Economics, 206, Article 104574.
Alolaywi, Y. (2021). Teaching online during the COVID-19 pandemic: Teachers’ perspectives. Journal of Language and Linguistic Studies, 17(4), 2022–2045.
Alon, T. (2020). The impact of COVID-19 on gender equality. NBER. https://www.nber.org/papers/w26947.
Alpert, W. T., Couch, K. A., & Harmon, O. R. (2016). A randomized assessment of online learning. American Economic Review, 106(5), 378–382.
Andrew, A., Cattan, S., Costa Dias, M., Farquharson, C., Kraftman, L., Krutikova, S., … Sevilla, A. (2020). Inequalities in children’s experiences of home learning during the COVID-19 lockdown in England. Fiscal Studies, 41(3), 653–683.
Azevedo, J. P., Hasan, A., Goldemberg, D., Geven, K., & Iqbal, S. A. (2021). Simulating the potential impacts of COVID-19 school closures on schooling and learning outcomes: A set of global estimates. The World Bank Research Observer, 36(1), 1–40.
Singh, B., Singh, P., Singh, U., Jangid, P., & Gupta, R. (2020). Students’ perceived stress and internet addiction during the lockdown in India. *Indian Journal of Private Psychiatry, 14*(1), 30-34.

Spitzer, M. W. H., & Musslick, S. (2021). Academic performance of K-12 students in an online-learning environment for mathematics increased during the shutdown of schools in wake of the COVID-19 pandemic. *PLoS One, 16*(8), Article e0255629.

Stelitano, L., Doan, S., Woo, A., Diliberti, M., Kaufman, J. H., & Henry, D. (2020). The Digital Divide and COVID-19: Teachers’ Perceptions of Inequities in Students’ Internet Access and Participation in Remote Learning. Data Note: Insights from the American Educator Panels. Research Report. *RR-A134-3 (ED609427).* ERIC. https://eric.ed.gov/?id=ED609427.

Teo, T. (2008). Pre-service teachers’ attitudes towards computer use: A Singapore survey. *Australasian Journal of Educational Technology, 24*(4).

Tomasik, M. J., Helbling, L. A., & Moser, U. (2021). Educational gains of in-person vs. distance learning in primary and secondary schools: A natural experiment during the COVID-19 pandemic school closures in Switzerland. *International Journal of Psychology, 56*(4), 566-576.

Toyoda, T. (1974). Use of the Chow test under heteroscedasticity. *Econometrica: Journal of the Econometric Society, 601–608, UNICEF.* (2020). Education and COVID-19 [Online]. Accessed at: https://data.unicef.org/topic/education/covid-19.

van de Werfhorst, H. G. (2021). Inequality in learning is a major concern after school closures. *Proceedings of the National Academy of Sciences, 118*(20), Article e2105243118. https://doi.org/10.1073/pnas.2105243118.

World Bank. (2020). Response to COVID-19: Preparing for school re-opening the case of China East Asia and Pacific education briefing note [Online]. Accessed at: http://documents.worldbank.org/curated/en/743891587996521873/pdf/Response-to-COVID-19-Preparing-for-School-Re-Opening-The-Case-of-China.pdf.

Yaghi, H. M. (2001). Subject matter as a factor in educational computing by teachers in international settings. *Journal of Educational Computing Research, 24*(2), 139-154.

Zhang, G. (2021). Differential impacts of COVID-19 school closures on college female and male students’ academic performance. Available at SSRN 3945380.