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Assessing inequality in the school closure response to COVID-19

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ABSTRACT

The spread of coronavirus disease 2019 (COVID-19) has caused school closures in most countries, affecting over 90% of the world's student population. School closures can widen learning inequalities and disproportionately hurt vulnerable students. We collected data on the exam scores of university applicants in China before and after a two-month period of school closure. We observe that students from rural, lower-income households are more negatively affected by school closures compared to their urban, higher-income counterparts. The inequality effect remains sizable in the admission exam three months after schools reopen. To strengthen the causal interpretation of the results, we investigate the scores in the previous graduating cohorts who did not experience school closure, and find no evidence of the change in scores over the same calendar period. Our study points to the urgent need to address the educational inequality caused by school closures.

1. Introduction

Since the onset of coronavirus disease 2019 (COVID-19), countries and municipalities have implemented a wide range of policies to slow down the pandemic, ranging from travel bans to school closures and home confinement. As a result, an unprecedented number of students have been suspended from attending schools in person. It is important to assess whether and how school closures affect inequality in learning outcomes across socioeconomic groups. This is to inform policy interventions that aim to prevent educational inequality from fermenting into persistent social inequality (Van Dorn, Cooney, & Sabin, 2019; von Braun & Zamagni, 2020).

During the school closure, the burden of education falls largely on parents. Research shows that families are the major sources of inequality in educational outcomes. The impact of family background on educational achievement has received much attention in the literature on inequality (Becker, 2009; Chetty, Hendren, Kline, & Saez, 2014; Cunha & Heckman, 2009; Sen, 1992; Xie & Zhou, 2014). A large part of the intergenerational transmission of education is attributed to differences in parental financial constraint and investments in children's human capital such as time input (Björklund & Salvanes, 2011; Black & Devereux, 2010; Cunha & Heckman, 2008; Guryan, Hurst, & Kearney, 2008). Family environments, especially at early ages, are major predictors of cognitive and non-cognitive abilities and health, which lay down a foundation for later educational attainment (Almond & Currie, 2011; Currie, 2009; Heckman, 2006). During school years, the achievement gap by family background continues to be widened during vacation periods in comparison to term periods (Cooper, Nye, Charlton, Lindsay, & Greathouse, 1996; Hattie, 2008).

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Many school systems offer home-based online learning during school closure. Earlier studies comparing online learning to traditional in-person classes have focused on higher education rather than elementary or secondary education (Bettinger, Fox, Loeb, & Taylor, 2017; Means, Toyama, Murphy, Bakia, & Jones, 2009). The flexibility and low cost of delivery of online learning have allowed it to reach educationally deprived populations (Christensen et al., 2014; Goodman, Melkers, & Pallais, 2019; Gulati, 2008). Regarding the abrupt adoption of online learning due to the pandemic, however, many have expressed concerns that it may raise extra challenges for disadvantaged students (Armitage & Nellums, 2020; Van Lancker & Parolin, 2020). For instance, inadequate distribution of internet infrastructure has limited these students' access to online learning resources (DiMaggio & Hargittai, 2001; Van Dijk & Hacker, 2003; Woolley, Sattiraju, & Moritz, 2020), giving rise to lower rates of class participation and homework completion (Chetty et al., 2020; Fishbane & Lara, 2020). Agostinelli, Doepke, Sorrenti, and Zilibotti (2022) provides a theoretical analysis of the impact of school closure and online education, allowing for changes to schooling, peer effects and parental investments. Their model predicts a large learning loss for children from low-income neighborhoods while those from high-income neighborhoods are unaffected.

A number of empirical studies have investigated impacts of COVID-19-induced school closures on education, and the findings vary across contexts (see the review of Donnelly & Patrinos, 2021). The meta-analysis by König and Frey (2022) which includes 18 studies from Europe, China and the United States points to a large average learning loss, and tentatively suggests that the loss is larger among younger age groups and for the initial lockdown. In terms of inequality effects, data on test score from European countries and United States suggest that school closures disproportionately affect the less advantaged students (Contini, Di Tommaso, Muratori, Piazzalunga, & Schiavon, 2021; Domingue, Hough, Lang, & Yeatman, 2021; Engzell, Frey, & Verhagen, 2021; Kogan & Lavertu, 2021; Maldonado & De Witte, 2022; Rose et al., 2021 and Schult, Mahler, Fauth, & Lindner, 2022). Those findings on learning outcomes resonate with the differences in learning time, activity, and access to school support across different socio-economic groups (Andrew et al., 2020; Grewenig, Lergetporer, Werner, Woessmann, & Zierow, 2021). Using test score data from Australian schools, Gore, Fray, Miller, Harris, and Taggart (2021) do not find any inequality effect by indigenous status, and the average leaning loss is also insignificant in their context. For Chinese secondary schools, Feng, Ioan, and Li (2021) document that the pre-existing gap between students in rural and urban areas has widened after online teaching, and Liao, Ma, and Xue (2022) find there is an increase in the test rankings of students with more highly educated parents following the school closure period.

While all of the above-mentioned studies feature primary or lower-secondary education, this paper uses unique data on educational outcomes of Chinese students in the final year of secondary education to assess inequality effects. This group of students are candidates for the national university admission exam, which is considered as a key channel for upward social mobility for students from disadvantaged backgrounds. The timing of the school closure is particularly important for this group of students, as it occurred during an intense period of exam preparation known as the "last sprint". During this period, students typically spend massive amounts of time and effort learning in school, making the school closure potentially a larger shock for them. Disadvantaged students, in particular, may be more affected by the closure due to their home environment being less conducive to learning and their parents having more limited bandwidth to support them academically and emotionally. Moreover, the re-opening of schools is only three months before the admission exam. This means that any education inequality arising at this stage is more directly related to the future income inequality for the cohort through university admission and therefore more important to be quantified.

We analyze the scores of 3373 university candidates from five highly ranked high schools who took two official mock exams (i.e., high-quality, centrally marked exams administered by local education authorities), one before and the other after the students had two months of school closure and home-based online learning. We observe that the students from rural families perform significantly worse after the school closure, compared to their urban peers. By contrast, in the control groups—3235 students in the 2019 cohort and 1969 students in the 2018 cohort—we do not observe such a pattern in similar exams during the same calendar period, suggesting that the observed pattern in 2020 is more likely due to school closure rather than a calendar time effect. Perhaps reflecting the higher intensity of school activities, the inequality effect for the Gaokao cohort is considerably larger than that observed in other secondary school grades, suggested by a rule-of-thumb calculation based on Liao et al. (2022).

This result is not driven by any particular school in the sample: while the inequality effect is insignificant for the two smaller schools, it is present if we look at the data of any of the three larger schools. For two out of the five schools, we have self-reported scores of the university admission exams three months after normal teaching resumed. The estimates for both schools are remarkably similar when we use the final exam compared to the mock exam. This suggests that the inequality effect likely has persisted and affected the final admission. The results are also robust when we proxy the socio-economic status by the average income of the student's township.

We further conduct three analyses to gauge the underlying mechanisms. First, while lacking data on COVID-19 exposure density at small geographic units, we use public attention—the search volume of COVID-19 related terms on a main search engine—as a proxy for general effects of the pandemic. We find that geographic variation in search volume related to COVID-19 does not explain the inequality effect, suggesting that our results are not likely to be driven by the general effects of the pandemic but the school closure. Second, we find that the inequality effect is larger in the subsamples of male students and students taking the arts track. One possible explanation is that those students are more sensitive to adverse home environment. Third, we look at a separate survey to examine home environment and learning behavior during school closure. We find evidence in support of digital divide whereby rural students rely on worse learning facilities (i.e., smartphones rather than computers or tablets, slow internet connection, etc.). Moreover, rural students also report lower participation and satisfaction for online learning.

Our research contributes to the understanding of the impact of school closures and brings education inequality to the attention of the academic community, policymakers, and the public. The human capital loss of under-privileged students can have a profound impact on their labor market prospects and thus long-term social inequality. Our empirical assessment of inequality in learning outcomes can help inform affirmative action policies in admission and call for more public spending to mitigate inequality, promote fairness and facilitate future social mobility.

2. Material and methods

2.1. Institutional background

Our main measure of socio-economic status is based on whether a student's household registration (*hukou*) is rural or urban. The hukou system categorizes China's population into a clearly defined spatial hierarchy, i.e., urban above rural and well-developed above less developed cities, in terms of resource allocation (Liu, 2005). The ratio of urban to rural income and consumption per capita has been substantial over the earlier decades (see for example, Knight & Song, 1999; Yang, 1999): as of 2019, the per capita disposable income and expenditure on education, culture, and recreation of urban households are 2.63 and 2.27 times of those for rural households (China Statistical Bureau, 2018, 2020).[1] In addition to the economic gap, there is a large gap in education between rural and urban hukou holders: as of 2008, 12% of rural hukou holders completed senior high school while the corresponding proportion was 51% among urban hukou holders (Meng, 2012). Moreover, the salience of the hukou status as part of social identity negatively affects the performance of under-privileged students in an incentivized cognitive task (Afridi, Li, & Ren, 2015).

The secondary education in China spans from the seventh to the twelfth grade. After first three years in middle schools, students take a high school entrance examination administered at municipal level (city, or county for rural area); each municipality contains both urban and rural areas and the admission does not depend on the hukou status. There is clear ranking of high schools and competition to attend higher-ranked schools (Ding & Lehrer, 2007). Upon graduation, students take the National College Entrance Examination (Gaokao), an annual examination and a pre-requisite for entrance into almost all institutions of higher education at the undergraduate level (Cai, Lu, Pan, & Zhong, 2019; Chen & Kesten, 2017).

Gaokao is commonly described as the "world's toughest exam" for the intense pressure and keen competition, and perceived as the most important life-changing opportunity for students and their families. There is a sizeable wage premium of attending one of the key universities, known as the national tier-1 universities (Li, Meng, Shi, & Wu, 2012); those who enter those elite universities by scoring just above the admission cut-offs are rewarded in terms of first-job wage after graduation, indicating that a few points in the exam matter greatly (Jia & Li, 2021).

Due to the importance of Gaokao, local education authorities offer students mock exam opportunities, to help them get a sense of Gaokao and to estimate their relative standings. These official mock exams mimic Gaokao and therefore have the same structure and coverage. The procedures are formal, and the scripts are centrally and blindly marked. The schedules are announced well ahead, and students from all schools in the region participate in the exams at the same time. Because the scores from mock exams provide reliable feedback of their academic progress, they are taken seriously by the students (Cai et al., 2019).

2.2. Data, summary statistics and empirical framework

We examine the effects of school closure on students graduating from the secondary education using data collected from five top-tier high schools in the prefectural region of Quanzhou, located in the Fujian province of China. Three of the schools are in the administrative subdivision of Quanzhou city, and two in Anxi county. Quanzhou is fairly representative of the coastal regions of China in terms of economic development. With respect to the indicators for education (e.g., the student-teacher ratio and the level of high school enrollment) and rural-urban disparity (e.g., the rural to urban income and consumption ratios), Quanzhou is similar to the provincial and the national averages. We provide a summary of social and economic characteristics of Fujian province, Quanzhou prefecture, Quanzhou city and Anxi county relative to China in Table S1 in the Supporting Information.

Every year, high-school students in Quanzhou prefecture have two formal mock exams, one in early January administered by the prefecture (*January exam*, henceforth), and one in late March administered by the province (*March exam*, henceforth). For the 2020 cohort, the school activities between the two exams were seriously disrupted by the COVID-19 crisis. Shortly after the January exam, the schools entered the winter break. In late January, the central government of China imposed the highest Major Public Health Emergency. All education institutions in the region were closed, and the high schools adopted online teaching when the spring semester began. The online teaching lasted for 8 weeks by the time of the March exam. All five schools in our sample offered online teaching and support following similar protocols overseen by the local education authority. Specifically, they all used similar platforms to support learning and had similar hours of online classes.

The March exam was carried out via an internet platform: prior to the exam, teachers individually checked that their students had correctly setup the connection; students answered the paper-based exam from home during a fixed time slot and were monitored using web cameras; at the end of the exam, students uploaded photos of their exam scripts to be marked. The normal school activities were restored in early April. Three months later, in July 2020, the students attended the Gaokao exam, which was postponed by one month due to the pandemic. The organization was otherwise the same as in the previous years. A detailed timeline with the dates of all the exams and major events is provided in Fig. S1 in the Supporting Information.

For all five schools, we have access to data on the two mock exams for both the 2020 cohort and the 2019 cohort. We observe the hukou status, as well as gender and subject stream (either science or arts) recorded in the schools' administrative systems. For three schools we have the additional data for the 2018 cohort. The availability of additional data by school is described in Table S2.

The exam scores are organized into student-level panel data. For all cohorts, we restrict the analysis to students who had attended

[1] The comparisons are by residential location because there are no official statistics on income by hukou status; residential location and hukou status corresponds closely, although they do differ for migrants.

both the January exam and the March exam, the two exams used in our main analysis. In all cohorts, the attendance rates are over 90% for both exams, and the March exam is slightly better attended. The attendance rate of the March exam in 2020 (96.2%) is very similar to 2019 (94.8%) and 2018 (96.3%), which indicates that there is unlikely to be any selection bias due to lack of access to the online exam. In all cohorts, around half of the students are from rural households (47.6% in 2020, 52.9% in 2019 and 48.7% in 2018). Full summary statistics for the three cohorts are reported in Panel A of Table S3.

The compositions of rural and urban students in terms of their potential Gaokao achievement differ across cohorts, as shown by the comparison of January scores. In 2018, the average January score of rural students is 0.527 SD lower than that of urban students, the difference reduces to 0.185 SD in 2019, and further reduces to 0.114 SD in 2020. Part of the difference between 2018 and the other two cohorts is attributed to the fact that the former sample includes three schools whereas the latter includes all five schools. We believe the compositional changes are more likely to arise from changes in the popularity of the schools in our sample, rather than some genuine difference between adjacent cohorts, since there was no change in the regional admission system. The popularity of a school may change year by year, differently for rural and urban students, due to the coverage of the advertisement campaign and the strategy to

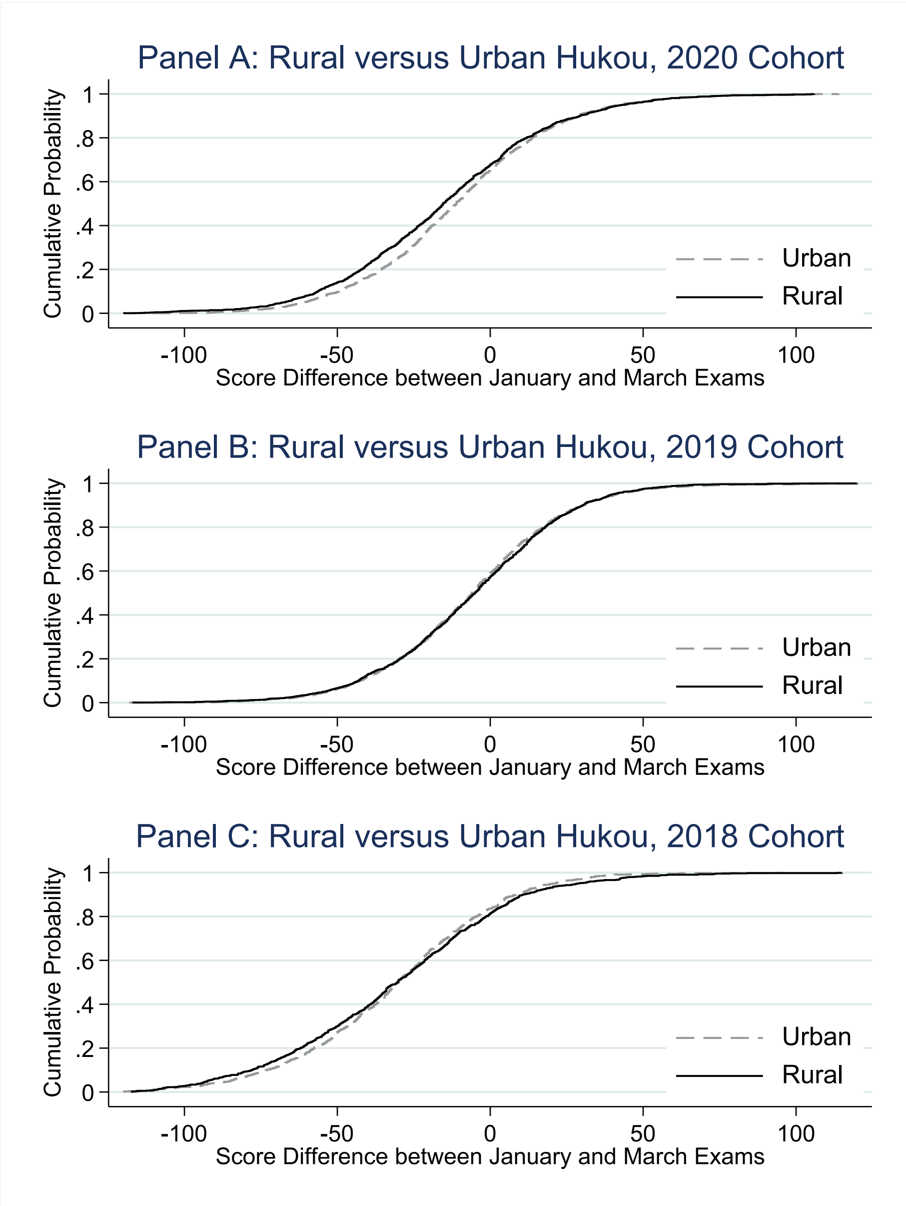

Fig. 1. Score difference between January and March exams by hukou status.
Notes: The scale for score difference is restricted from − 120 to + 120; a very small number of observations fall outside this range 22 (0.65%) in the 2020 cohort, 18 (0.56%) in the 2019 cohort and 17 (0.86%) in the 2018 cohort. We do not exclude these observations from the analysis.

attract high-performing students.

To investigate the effect of school closure, we conduct a triple difference estimation as our main identification. Specifically, we use the cohort (i.e., 2020 versus 2019/2018), hukou status (i.e., rural versus urban) and time (i.e., January versus March exam) variations. Our identification assumption is that, across the January and March exams, the relative performance of rural and urban students in the treatment cohort, 2020, trends in the same way as the relative performance of rural and urban students in the control cohorts of 2019 and 2018, in absence of the school closure. In other words, we assume that if there are any difference in the relative performance trends of rural and urban students, such difference is the same across cohorts. The triple difference specification is as follows:

$$\begin{aligned} Y_{it} = & \beta_0 + \beta_1 1[year = 2020] \times Rural_i \times March_t + \beta_2\, Rural_i \times March_t + \beta_3 1[year = 2020] \times Rural_i + \beta_4 1[year \\ & = 2020] \times March_t + \beta_5 1[year = 2020] + \beta_6 March_t + \beta_7 \times Rural_i + \delta X_i + \varepsilon_{it} \end{aligned} \tag{1}$$

where i denotes student, and t denotes the time of the exam. $1[year = 2020]$ is an indicator for being in the "treated" 2020 cohort; $Rural_i$ is an indicator for rural hukou status; $March_t$ is an indicator for March exam. The outcome variable, Y_{it}, is the exam score. The coefficient of interest β_1 shows whether the relative performance of disadvantaged rural students changes between the two exams in year 2020 differ from those relative changes between two exams in year 2019 and 2018. β_2 through β_7 are the estimates of the double interaction terms and linear terms. The other control variables, X_i, include gender, subject stream, and school fixed effects. ε_{it} is the idiosyncratic error term. Throughout the paper, we cluster the standard errors at student level to account for any heteroskedasticity and serial correlation.

3. Results

We first provide an overview of how the school closure affected the exam scores of different socioeconomic groups. Fig. 1 plots the empirical cumulative distribution function of the change in scores between January and March exams by hukou status for the three cohorts. For the 2020 cohort, the curve for rural students lies to the left of the curve of urban students, indicating that rural students exhibit more negative changes between March and January. Such a difference is not present in the data of the 2019 cohort and 2018 cohort, as the distributions of the rural students closely match their urban counterparts. The data from previous cohorts confirm that the scores for rural and urban students are expected to move in parallel under normal school activities, so the change in relative performance observed for the 2020 cohort is likely attributed to the school closure.

Table 1 displays a quantitative analysis of the relative performance of disadvantaged students by estimating Eq. (1). We observe that the school closure induces a decline in the relative performance of rural students. Column (1) shows that the rural-urban difference in scores between January and March of 2020 drop by 5.828 points ($P < 0.001$) which is a sizeable effect of 0.071 SD, relative to the rural-urban difference in scores between January and March of 2019 and 2018. Column (2) reports the results with only the 2019 cohort as the comparison group, and the triple-difference estimate remains negative and statistically significant. Both columns also show that the rural-urban difference remain constant between January and March in the previous cohorts: the point estimates are 1.120 pooling the 2018 and 2019 cohorts ($P = 0.267$) and -0.059 for the 2019 cohort alone ($P = 0.960$).

We report a number of alternative specifications in Table S4. The results are similar if we estimate Eq. (1) without controlling for subject type, gender, and school fixed effects or if we standardize the scores within the exam and the subject stream. The results are also robust if we control for fixed effects crossed between year-exam, subject stream and school or if we standardize the scores by year-exam, subject stream and school, suggesting the inequality effect is driven by within-school comparisons. This is not surprising because our sample of schools consists of only top-tier schools in the region. We note that in other settings, the between-school variation can be a leading cause of inequality effect. For example, using a sample of ninth-grade students in Guangxi province, Clark, Nong, Zhu, and Zhu (2021) show that schools offering online teaching achieved significantly better student performance compared with the ones offered no online learning support.

A comparison to the literature shows that the size of inequality effect for the Gaokao cohort is significantly larger than other secondary school grades. Using a panel of exam scores of Grade 7 students in junior high schools, Liao et al. (2022) find that an additional year of parental education translates to a relative advantage of 0.006 SD after school closure (95% CI 0.001 to 0.010). Urban households have higher levels of education compared to the rural ones – the provincial-level disparity in 2019 is 1.7 years (National Bureau of Statistics of China, 2020). We lack data on parental education for our sample; it is plausible that the difference may be narrowed by the selection at high-school entrance. Nevertheless, a difference in parental education of 1.7 years would only project to a rural-urban inequality effect of 0.010 SD (95% CI 0.002 to 0.017), whereas our estimates are between 0.061 and 0.081 SD (Table S4, 95% CI 0.021 to 0.101 for the most conservative estimate).

We check for heterogeneity in the inequality effects across schools. Fig. 2 presents the estimate of Eq. (1) by school. The pooled estimate lies within the confidence intervals of all schools. The estimated inequality effects are significantly negative in the three larger schools with 700–900 students per cohort (School 1, School 3 and School 5), and not significantly different from zero for the two smaller schools with around 400 students per cohort (School 2 and School 4). We note that the largest inequality effect which is about twice the size of the pooled estimate is observed for School 5, a large school located in the relatively rural Anxi county.

We have additional Gaokao data for School 1 and School 4. Due to the confidentiality policies of the education authority, Gaokao scores are not directly accessible from the administrative systems. Instead, for those two schools we get access of self-reported Gaokao data for 99.0% of students who took the January exam in 2020 and 83.9% in 2019. In both cohorts, the observation rate of Gaokao data is similar for rural and urban students. We provide summary statistics of this Gaokao sample in Panel B, Table S3.

We use the same framework to analyze Gaokao results as we do for mock exam results. That is, for each student in the Gaokao

Table 1
Effects of school closure on inequality.

	(1)	(2)
	Control	Control
	2019&2018	2019
1[year = 2020]*Rural*March Exam	−5.828***	−4.648***
	[1.613]	[1.713]
Rural*March Exam	1.120	−0.059
	[1.009]	[1.162]
1[year = 2020]*Rural	10.696***	7.505**
	[2.957]	[3.247]
1[year = 2020]*March Exam	7.107***	−3.151**
	[1.133]	[1.227]
1[year = 2020]	4.704**	0.657
	[2.382]	[2.344]
March Exam	−16.496***	−6.239***
	[0.713]	[0.855]
Rural	−8.952***	−7.339***
	[1.822]	[2.290]
School Fixed Effects	YES	YES
Baseline Controls	YES	YES
Observations	17,154	13,216
Adjusted R-squared	0.403	0.419

Notes: Baseline controls include gender and subject stream. Standard errors are clustered by student. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

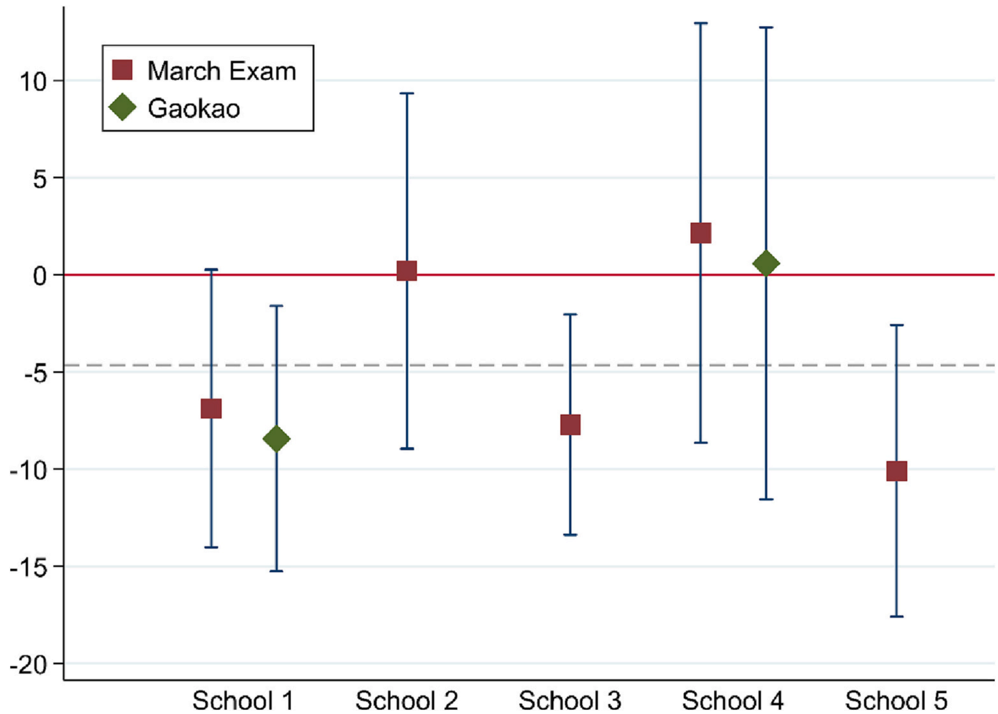

Fig. 2. Effects of school closure on inequality estimated by school.
Notes: The square markers are coefficients of the triple interaction term in Eq. (1) estimated separately by school, using the data of 2019 and 2020 cohorts which are available for all schools. The dashed line is the pooled estimate reported in Column (2) of Table 1. The diamond markers present the analogous estimates replacing March Exam by Gaokao results for the students in School 1 and School 4 who attended the January Exam and reported their Gaokao results to the school. The brackets indicate 95% confidence intervals.

sample, we use observations from their January exam and their Gaokao exam, and estimate Eq. (1) replacing the March exam with the Gaokao exam, plotted in Fig. 2 (regression results reported in Table S5). When we pool School 1 and School 4, the inequality effect estimated using the March exam is smaller than in the full sample and insignificant (−2.660 points, $P = 0.394$), and so is the inequality effect estimated using Gaokao data (−2.981 points, $P = 0.377$). The estimates for School 4 are close to zero for both mock exams and

Gaokao. For School 1 which sees a marginally significant inequality effect in the mock exams (−6.889 points, $P = 0.059$), the inequality effect for Gaokao is also significant and of similar magnitude (−8.440 points, $P = 0.015$). These results tentatively suggest that the inequality effect we observe in the mock exams generalizes and persists when it comes to the high-stakes exam. In addition, it is unlikely for the inequality effect for the March exam to be attributed to the online exam format.[2]

While hukou status is an important measure of SES, it may have a noisy correlation with household income. We do not observe student-level household income in our data, but we do observe the township-level per capita income. For the two schools in Anxi county, we observe the students' residential locations at the township level. We provide summary statistics of this sample in Panel C, Table S3. There is large income variation among the 24 townships in Anxi county: the average annual per capita income in 2015 and 2016 is 10,683 yuan in the poorest township, or 41% of the income of the richest township, 26,332 yuan.[3] The per capita income of the township provides a more granular measure of socio-economic status than hukou status.

We observe that there is a strong positive correlation between the township level income and the change in exam score between March and January 2020, as plotted in Panel A of Fig. 3. Students from lower-income townships on average have a larger fall in test score than those from higher-income townships. Such a relationship is not observed in the 2019 cohort, displayed in Panel B of Fig. 3. The results are corroborated by the regressions reported in Table S7. Compared with the relative score trend between January and March of 2019 cohort, 1 % decrease in township average income is associated with a more negative score change between two exams by 0.137 points in the 2020 cohort ($P < 0.001$). We also consider a specification which including relevant triple and double interactions of $1[year = 2020]$ and March with both rural hukou status and township average income. We find an inequality effect only for township average income, and the triple-difference estimate using hukou status becomes insignificant. These results indicate that school closures hurt students with lower socioeconomic status proxied by average income of their township, and that the income difference between rural and urban households can explain much of the inequality effect.

The reduction in scores for disadvantaged students can have an appreciable impact on their chances of being admitted to better universities. According to the distribution of Gaokao results for the 2020 cohort published by Fujian Province, one point difference in the score at the median leads to around 0.4 percentage point difference in ranking, so a disadvantage of 5–6 points will decrease the students ranking by 2 to 2.4 percentage points at median. We note that, with limited access to Gaokao data, this inference is based on the March exam, although it is reassuring that, for the two schools that we have data of, the estimates are similar between the March exam and Gaokao.

4. Underlying mechanisms

In this section we discuss potential mechanisms underlying the differential effect of the school closure by socioeconomic status. We first present suggestive evidence that our observed inequality effect is more likely to be driven by the school closure, rather than general effects of the pandemic. We further use data from a separate survey to examine home environment and learning behavior during the school closure.

4.1. General effects of the pandemic

While the effects of the COVID-19 pandemic are far-reaching and profound, in retrospect, its impact on Quanzhou region is relatively small. As of 11 June 2021, the number of officially reported COVID-19 cases in the region is 47 (6.2 per million of the population) and the number of deaths is zero. The 2020 GDP growth of the region is positive at 2.9%, lower than the 2019 growth of 8.0%. It is possible that the pandemic and the lockdown have caused uncertainty and income decline disproportionately among disadvantaged households, which affects the children's education outcomes.

To test this possibility, we construct a measure of public attention to the pandemic at township level for the residential location sample to proxy the impact of the pandemic (exposure density at township level is not available). We collect data from Baidu Index for the search volume on the main search engine used in China, which is available by geographic area (the smallest unit is prefecture). For each of the 24 townships, we obtain the daily search volume within Quanzhou prefecture for the term "*xinguan*" (the most-used Chinese name of COVID-19) plus the name of township, averaged over the period from 25 January (the date of activation of the highest Major Public Health Emergency) to 28 March 2020 (the date of March exam).[4] Fig. 4 shows that the correlation between

[2] For School 1 in our sample, we also have additional data for an in-person mock exam in April 2020, right after the reopening. This additional exam was part of the education authority's response to the interruption of the COVID-19 crisis, hence there was no corresponding exam for the 2019 cohort. We estimate the inequality effect by comparing the January exam to the April exam with a difference-in-differences specification (Table S6). Although the inequality effect is slightly and insignificantly smaller than when we use the March exam, it remains sizeable and significant. Therefore we believe that the exam format is not a key contributor to the inequality effect.

[3] The most up-to-date township-level income statistics for Anxi county are for 2015 and 2016 (Anxi County Local Chronicles Compiling Committee, 2016, 2017). We take the average between the two years to reduce noise, although the results are not sensitive if we use either 2015 or 2016 statistics.

[4] It is possible that a rural, less developed township has fewer internet users and hence a lower COVID-related search volume. We also use a relative search volume, the COVID-related search volume divided by the weather-related search volume, which leads to very similar results as the absolute search volume. It turns out that in our sample the search volumes for COVID and weather are not correlated with the annual per capita income.

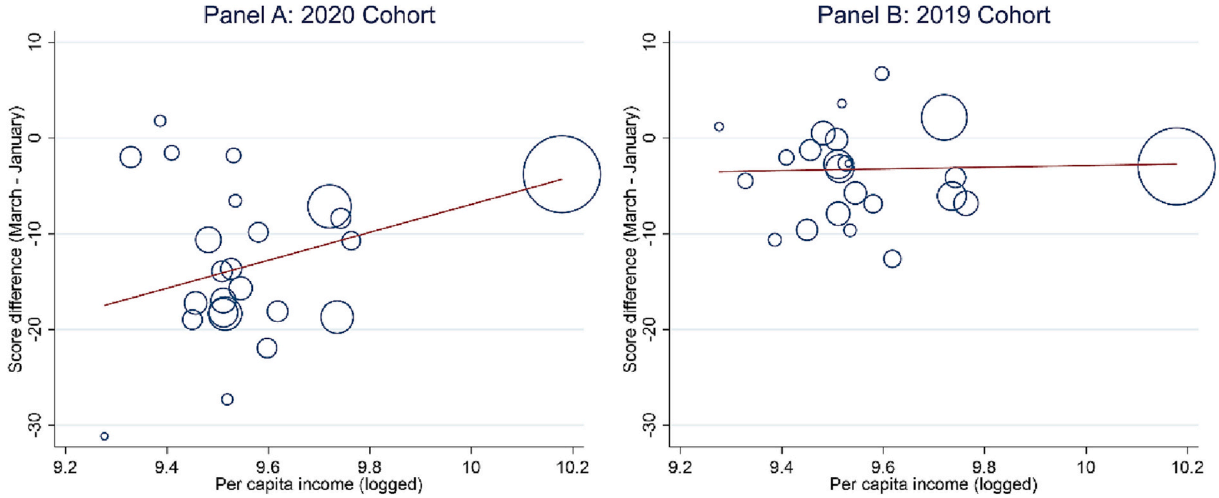

Fig. 3. Relationship between township-level average income and score difference.
Notes: Each circle represents a township; the size of the circle indicates the number of students in our sample who reside in the township. The linear relationship between per capita income and the score difference is fitted using data of 1165 and 1202 students in the 2020 cohort and 2019 cohort.

individual-level score change and COVID-19-related search volume of the residential township is close to zero. Adding the search index and its triple and double interactions with March exam and Year 2020 into the model has little impact on the estimated inequality effect for rural students (Table S8). Therefore this analysis does not provide evidence that the inequality effect we document is driven by the general effects of the pandemic. This may not be surprising because in our context the short-term general impacts of the pandemic is limited.

4.2. Subsample analysis

Table 2 explores whether the rural-urban inequality effects are more concentrated in certain subsamples to shed light on potential mechanisms. A comparison of columns (1) and (2) shows no significant difference in inequality effects by gender. Adolescent males are typically more responsive to adverse home environments (e.g. Autor, Figlio, Karbownik, Roth, & Wasserman, 2019; Bertrand & Pan, 2013), potentially exacerbating the rural-urban disparity for them. However, during the COVID-19 outbreak, adolescent females in China and other Asia Pacific countries are documented to experience higher levels of depression and anxiety (Duan et al., 2020; Wang et al., 2021) and less stress resilient (Zhang et al., 2020) than males. These factors may contribute to the lack of significant gender difference observed. Columns (3) and (4) show that the inequality effects are larger for Arts track than for Science track. This finding may be reconciled with the expectation that home environment is more important to students on the arts track, who tend to have lower locus of control and self-esteem (e.g., Mendolia & Walker, 2014).

4.3. Home-based learning environment and behavior

We use additional survey data to test whether rural and urban students have different home-based learning environments and behavior during the period of school closure, which may explain the difference in their learning outcomes. The Quanzhou Educational Bureau distributed a short online survey on the online learning experience of school students, which covered all primary and secondary schools. The survey was open from 28 February to 4 March 2020. Both parents and students were invited, and the participation rate is above 10% for high-school students and parents. There are 4404 responses from final-year high-school students or their parents. The survey asked whether the respondent's residential location is rural or urban, which is not equivalent to but corresponds strongly with the hukou status. The full questionnaire is available in Supporting Information S1 Appendix. The proportion of rural residents is 52.6% in the survey sample, which is comparable to the proportion of students with rural hukou in our main sample. We compare the rural and urban responses in Table 3.

The participation rate and effort differ for urban and rural parents, indicating that rural parents have paid less attention to their children's online learning situation than urban parents. Significantly fewer rural parents filled in the survey for their children: only 27% of the rural responses are from parents, compared to 45% among urban responses ($P < 0.001$). The survey effort can be measured by the amount of time spent on the survey and whether the respondent write suggestions in the open field of the survey. Rural respondents put in lower effort than urban respondents ($P < 0.001$ for response time and $P = 0.032$ for the proportion writing suggestions), and the difference is driven by parents rather than students (Table S9 reports the separate rural-urban comparison using the responses by students and parents).

The online learning of rural students differs from that of urban students in two main aspects (the findings are robust if we focus on the responses reported by students and exclude those by parents, see Panel B of Table S9). First, rural students were worse off in terms

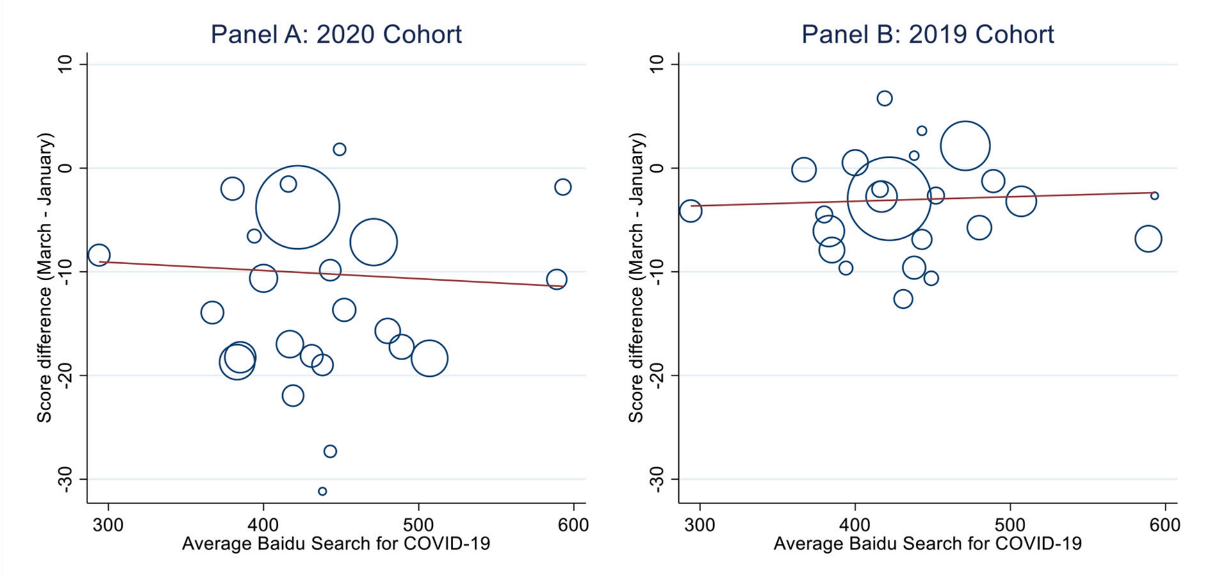

Fig. 4. Relationship between township-level search for COVID-19 and score difference.
Note: Each circle represents a township; the size of the circle indicates the number of students in our sample who reside in the township. The horizontal position indicates the daily search volume within Quanzhou prefecture for the term "*xinguan*" (the mostly used Chinese name of COVID-19) plus the name of township, averaged over the period from 25 January (the date of activation of the highest Major Public Health Emergency) to 28 March 2020 (the date of March exam). The linear relationship between search volume on Baidu search engine and the score difference is fitted using data of 1165 and 1202 students in the 2020 cohort and 2019 cohort.

Table 2
Subsample analysis for rural-urban inequality.

	(1)	(2)	(3)	(4)
	Male	Female	Arts Track	Science Track
1[year = 2020]*Rural*March Exam	−6.395***	−4.450**	−10.235***	−3.078
	[2.399]	[2.167]	[2.610]	[1.976]
Rural*March Exam	−0.378	1.852	5.460***	−0.994
	[1.505]	[1.351]	[1.633]	[1.219]
1[year = 2020]*Rural	10.756**	10.265***	20.747***	5.416
	[4.623]	[3.730]	[4.296]	[3.784]
1[year = 2020]*March Exam	10.698***	3.439**	2.554	9.183***
	[1.634]	[1.564]	[1.908]	[1.381]
1[year = 2020]	3.556	7.424**	−3.969	9.357***
	[3.658]	[3.047]	[3.431]	[3.095]
March Exam	−18.806***	−14.209***	−6.009***	−21.581***
	[1.046]	[0.966]	[1.141]	[0.877]
Rural	−6.317**	−10.664***	−13.387***	−6.430***
	[2.986]	[2.183]	[2.464]	[2.406]
School Fixed Effects	YES	YES	YES	YES
Baseline Controls	YES	YES	YES	YES
Observations	8264	8890	5514	11,640
Adjusted R-squared	0.411	0.409	0.471	0.402

Notes: Baseline controls include gender and subject stream. Standard errors are clustered by student. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample includes all three cohorts, i.e., both 2019 and 2018 are included as control. The estimates which exclude the 2018 cohort give similar findings.

of hardware and equipment for online learning. Only 33% of urban students had their smartphone as the single main device (while the rest had access to tablets, computers, or a TV screen), and the proportion was 48% among rural students ($P < 0.001$). Most of both rural and urban students encountered technical problems with online learning (e.g., getting disconnected, internet lagging), but rural students were slightly more likely to have those problems compared to urban students (24% of rural students and 27% of urban students reported they never came across any problems, $P = 0.027$).

Second, rural students spent less time on online learning than urban students, and they were less likely to participate in the interactive part of online learning or consider the online interactions as effective. The average study time for rural students was 4.85 h,

Table 3
Summary of online learning survey by residential location.

	Rural $N = 2316$	Urban $N = 2088$	Difference (Urban-Rural)	*p*-value
Prop. of responses by parents	0.27	0.45	0.17	0.000
Response time (minutes)	2.72	3.66	0.94	0.000
Prop. with suggestions[a]	0.14	0.17	0.02	0.032
Prop. use smartphone only[b]	0.48	0.33	−0.15	0.000
Prop. report no difficulty[c]	0.24	0.27	0.03	0.027
Daily length (hours)[d]	4.85	5.21	0.36	0.000
Method of online learning: prop. Use as a main method				
Live broadcast	0.94	0.93	−0.01	0.376
Recorded lessons	0.47	0.37	−0.10	0.000
Course material packages	0.27	0.23	−0.04	0.002
Online discussions	0.39	0.47	0.08	0.000
Homework assignments	0.70	0.68	−0.01	0.296
Effectiveness by activity: prop. Report effective				
Previews	0.31	0.34	0.03	0.033
Lectures	0.29	0.35	0.06	0.000
Revisions	0.76	0.76	0.00	0.791
Discussions	0.45	0.55	0.09	0.000

Notes: We report *p*-values from proportion tests for the proportions and *t*-tests for continuous variables.

[a] Respondents who wrote in the open field for suggestions at the end of the survey.

[b] Respondents who chose smartphone as their only "main device used for online learning" and none of the other devices (options include tablet, computer, and TV screen).

[c] Respondents who chose "none" when asked what problems they encountered during online learning. The other options include lack of equipment, disconnected for audio, disconnected for video, internet lagging, too many chat messages for the teachers to address, and lack of data balance.

[d] Respondents were asked how long they spent on online learning every day. The original responses are in six bands: <20 min, 20–40 min, 40–60 min, 1–3 h, 3–6 h, and over 6 h. The responses are converted to the mid-point of the band for the first five options and 8 h for "over 6 hours" to facilitate a quantitative comparison.

compared to 5.21 h for urban students ($P < 0.001$). Respondents were asked to indicate their main methods for online learning (options include live broadcast, recorded classes, learning material packages, online discussion, and homework). Compared to urban students, rural students were more likely to take recorded classes (47% versus 37%, $P < 0.001$) and use learning material packages (27% versus 23%, $P = 0.002$), but less likely to participate in online discussion (39% versus 47%, $P < 0.001$). Respondents were also asked to indicate whether online learning was effective for previewing new course material, taking lectures, conducting revision, and taking discussions. The largest difference is observed for discussions: 45% of rural students found them effective, compared to 55% of urban students ($P < 0.001$).

We note two differences between the survey sample and test-score sample used in our main analysis. First, the survey sample consists of graduating students from any of the high-schools in the region whereas our test-score sample features only top-tier schools. Second, the survey participation is voluntary and subject to self-selection, whereas the test score data were recorded for all students in the sampled schools. The two differences may have created opposite forces on whether findings from the survey sample overstate or understate the rural-urban difference in the test-score sample: the students in the top-tier schools and those who choose to participate in the survey both tend to be less disadvantaged. Although we cannot determine the overall direction of bias, the size of differences in home environment and online-learning participation documented by the survey sample is large enough for us to put those factors forward as likely contributors to the observed inequality effect.

5. Discussion

The implications of prolonged school closures for exams and assessments have been of great concern to students, teachers, parents, and policymakers. Central to this concern is the issue of fairness, especially for high-stakes exams. We investigate the impact of school closures on inequality by comparing scores on mock exams for university applicants in schools in a coastal region of China before and after school closure. We observe that school closure has a detrimental effect on the test scores of the students from rural and low-income family backgrounds. This effect may decrease these students' chances of getting into their desired universities.

We believe that our evaluation provides a lower-bound estimate of the impact of school closures on inequality for several reasons. First, while hukou status captures important aspects of socioeconomic status including income, parental education, and occupation, it is a noisy binary classification and we cannot pin down the importance of these factors. Nevertheless, when we use township income as an alternative measure of socioeconomic status, we find a similar effect. Second, the schools in our sample are top-tier schools in the relatively-abundant coastal region of China and even the most disadvantaged students in our sample have access to online learning. Given this homogeneity of schools in our sample, we are only able to document the inequality effect by comparing students within the schools. In the regions that some schools do not provide online classes, the inequality effect can be much larger due to the concentration of disadvantaged students in low-quality schools and the between-school comparison (see e.g., Clark et al., 2021). Finally, we note that longer and reoccurring school closures can have larger effects on inequality, as disadvantaged students may be less resilient to such risks and become more likely to drop out from their education.

The results of the present study call for considerations of various policies to reduce educational inequalities caused by school closures during the current pandemic. First, there is an urgent need to provide support for disadvantaged students in terms of facilities and other aspects of readiness for online learning. Second, it would be desirable to consider alternative exams and assessments for the given context, institution, and culture. Finally, affirmative action should be put in place to take into consideration the adverse impact of school closures on vulnerable students.

To this end, given that school closures is likely to be part of the strategies to control the pandemic in many countries, it would be highly valuable to have a comprehensive evaluation of the effects on various domains such as child development and mental health, as well as across different countries and cultures.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2023.102008.

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