

Significant declines in standardised test scores due to COVID-19 school closures disproportionately affect vulnerable students: A replication analysis using data from the United States and a case study on the Netherlands*

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Abstract

School closures due to the COVID-19 pandemic have raised significant concerns about the consequences on student learning and achievement gaps. This paper replicates a data analysis of the scope of school closures in the United States in the 2020-2021 school year, the inequitable distribution of such closures by demographic characteristics and the resultant declines in pass rates on standardised tests in mathematics and English Language Arts (ELA) of students in grades 3-8 across 11 states. We apply secondary research regarding the scope of school closures in the Netherlands in same year and the declines in national examination scores in reading, spelling and mathematics of Dutch students in grades 4-7. Although the Netherlands is regarded as ‘best-case’ scenario, with a short lockdown, equitable school funding, and high degree of technological preparedness, we find that Dutch students still experienced a significant learning loss, equivalent to one-fifth of that of the United States, with a disproportionate impact on vulnerable students. These findings suggest that COVID-19 school closures imposed significant costs of learning loss and widened inequality gaps in the United States and the Netherlands, with impacts likely larger in countries disenfranchised by weaker infrastructure or longer closures.

1 Introduction

On March 11, 2020, the World Health Organisation (WHO) declared the COVID-19 outbreak a global pandemic, urging all countries take action in detecting infection and limiting spread (WHO 2020). Shortly after the announcement, many countries began to implement measures to reduce COVID-19 contagion and transmission. In spite of the general effectiveness of such measures in saving lives (Wu et al. 2020), they imposed severe disruptions to the lives of children and adolescents. These included delayed healthcare provision, decreased contact with peers and relatives, routine modification, and diminished sense of well-being (Richard et al. 2023). Among the most significant disruptions, and the topic of this paper, was the closure of schools in favour of virtual learning.

Before the pandemic, there was a modestly-sized economic literature on the impact of school closures on learning, with data generally drawn from short-term episodes such as teacher strikes (Jack and Oster 2023). It was widely observed that time outside of school caused loss of literacy and numeracy skills, more so among the marginalised, and widened student achievement gaps (Aurini and Davies 2021). These findings are certainly suggestive of the possible effects of COVID-19 school closures

*Code and data are available at: <https://github.com/AbbassSleiman/COVID19-US-School-Closures>; Replication on Social Science Reproduction platform available at: <https://www.socialsciencereproduction.org/reproductions/1616/index?step=0>

on student learning. However, as the pandemic’s disruptions typically surpassed previous episodes of school closures, the scope for inference from earlier works is limited (Jack and Oster 2023). A paper by Jack and Oster, “COVID-19, School Closures, and Outcomes” (2023) published in American Economic Association’s *Journal of Economic Perspectives*, sought to address this gap, by focusing on emerging short-term evidence of the impact of COVID-19 school closures on academic performance.

In studying the scope of school closures across the United States, they reported that the country experienced, on average, one of the highest number of days of school closed between January 2020 to December 2021 worldwide (Jack and Oster 2023). Jack and Oster (2023) also found that the duration of school closures varies with local demographic characteristics, with more disadvantaged districts facing more prolonged closures. The study population was grade 3 to 8 students across 11 major American states, being Colorado (CO), Connecticut (CT), Massachusetts (MA), Minnesota (MN), Mississippi (MI), Ohio (OH), Rhode Island (RI), Virginia (VA), Wisconsin (WI), West Virginia (WV) and Wyoming (WY). The estimand was the impact of COVID-19 closures on academic performance. They found considerable declines in test scores during the 2020-2021 academic year, with declines larger in school districts with less in-person instruction (Jack and Oster 2023). On average, pass rates fell from 2019 to 2021 by an average of 12.8 percentage points in mathematics and 6.8 in English Language Arts (ELA) (Jack and Oster 2023).

Our paper seeks to assess the robustness and generalisability of Jack and Oster’s work. We successfully replicate and extend three of its major research claims:

- (1) With respect to the world, the United States faced second highest number of days of school closed between January 2020 to December 2021, with a mean number of days of 667.
- (2) Access to in-person education was unequal across various demographic characteristics, being significantly correlated with an area’s ethnic composition and broadband usage. In general, more disadvantaged districts spent more of the school year in virtual schooling.
- (3) School closures contributed significantly to the decline in students’ pass rates in mathematics and ELA in the 2020-2021 school year. Changes in ELA scores were smaller than mathematics scores, but significantly larger in districts with larger populations of students who are Black, Hispanic, English Language Learners (ELL) or eligible for free and reduced price lunch (FRPL).

We also apply a Dutch-facing lens, examining the extent of school closures and the impact on student learning, in a country whose pandemic circumstances were regarded as most favourable for students (Engzell, Frey, and Verhagen 2021). In spite of a short lockdown, equitable school funding and high degree of technological preparedness, we discuss how Dutch students still suffered a loss of the equivalent of one-fifth of a year of education and how the effects were distributed unequally according to student demographics. Throughout, our investigation is conducted using the open-source statistical programming language R (R Core Team 2022), with functionalities from `tidyverse` (Wickham et al. 2019), `janitor` (Firke 2021), `knitr` (Xie 2023), `here` (Müller 2020), `kableExtra` (Zhu 2021), `DiagrammeR` (Iannone and Roy 2024), `readxl` (Wickham and Bryan 2023) and `patchwork` (Pedersen 2024).

This paper is structured, as follows. In Section 2, we address the sources of the data sets in the original paper, the methodologies used to collect them, and highlight key features. In Section 3, we conduct a replication of the original study to confirm the robustness of its findings and to design scientific figures that permit a more effective data visualisation. In Section 4, we assess the relevance of these findings to the Netherlands. We compliment this discussion by addressing ethical implications and limitations of the original research, and by giving directions for future analysis.

2 Data

2.1 Source

For this paper, the raw data from the “COVID-19, School Closures, and Outcomes” paper were used (2023), published in the American Economic Association’s *Journal of Economic Perspectives* (AEA 2024). To investigate the degree of school closures in the United States, and their attendant effects on children, they pose the following three questions:

- (1) Relative to the global picture, what is the extent of school closures in the United States?
- (2) What are the demographic patterns underlying these closures? Namely, how are the number of days of school closed correlated with ethnicity, unemployment rate and political leanings at the district- or county-level?
- (3) What is the short-term impact of school closures on student academic performance and learning inequalities?

Whilst the Jack and Oster’s paper uses a range of data files, we only use some of these files. The specific files that were used, including their sources and a description of how the data is collected is given below.

2.1.1 Abbass’ data sets

2.1.2 Average Virtual Days By Local Characteristics

`District_Overall_Shares.csv`

This data set is available from the COVID-19 School Data Hub (Hub 2021), and provides information on the percentage of the school year that was spent in person, hybrid, or virtual. The data is given for each district, and includes the district’s NCESDistrictID and the state they are a part of.

`nces_district_directory_2018.dta`

This data set is available from the National Center of Education Statistics (NCES 2021). This data set provides a variety of metrics for each district, including the state and county they are a part of, as well as their NCES district ID.

`nces_district_enrollment_2018_2020.csv.zip`

This data set is available from the National Center of Education Statistics (NCES 2021). This data set provides a variety of metrics. For each district, the total number of students enrollment is reported and is split by the grade (ranging from Kindergarten to Grade 12), by the sex (Male and Female), and by the race (American Indian or Alaska Native, Asian, Black, Hispanic, Native Hawaiian or other Pacific Islander, or Two or more races). This information is reported for the years 2018, 2019, and 2020, and also includes the district’s NCES district ID and the state that they are a part of.

The original file was a Stata file, however, to reduce the size, data on 2018 and 2019 was first removed, since they were not required for our paper, before then converting the file to a csv file, and then compressing it into a zip file. This file was then processed within R.

`broadband_data_2020October.csv`

This data set is available from Microsoft’s “United States Broadband Usage Percentages Dataset” Github Repository (Kahan 2020). The data is for October 2020, and gives the broadband usage for each county in the United States, as well as the state that the county is a part of.

2.2 Methodology

2.2.1 Datacleaning for Abbass' Figure 1

2.2.2 Average Virtual Days By Local Characteristics - Figure 2

The purpose of (figure2?) is to explore the correlations between certain district and county characteristics, and the average number of virtual school days for the respective district or county. Specifically, we look at broadband usage by county, and the shares of four races (White, Black, Asian, Hispanic) by district. For each county or district, we assign “high” or “low” depending on if their level for the characteristics being explored is above or below their state’s median, respectively. By doing so, we allow for the results to be driven by a variation within states, as opposed to variation across states.

We start by using `nces_district_enrollment_2018_2020.csv.zip`. As previously mentioned, this data set splits the total enrollment into various categories. We start by converting the columns into the numeric class as appropriate. Some enrollment cells did not have a value, indicating that data was not collected for that specific metric. These occurred a handful of times for certain races within certain districts. These NAs were replaced with 0s. For our paper, we are concerned specifically with race. Thus, for each district, we calculate the total number of White, Black, Asian, and Hispanic students enrolled. Given the structure of the data, this is done by summing the total enrollment per race for Male and Female for each district. Next the total enrollment for the whole district was calculated, before then calculating the share of total enrollment that each race comprises.

The data above was then separated into different tables for each race. For each race, we then classified the district as either “High” or “Low” depending on if their share was above or below their respective state’s median. Using this data, we were now interested in the number of virtual days that each of these districts had. This information was available in the `District_Overall_Shares.csv` data set. Given that the US average number of school days per year is 180, the percentage for `share_virtual` was multiplied by 180 for each district.

Next, the aforementioned data for each race that separated the districts into quantiles, and the data for the number of virtual days per district were merged. This results in some NAs being produced since the data set on race had more districts than the data on the number of virtual days. Given the lack of data, all NAs were dropped. Finally, the number of virtual days for the “High” quantile and the “Low” quantile were averaged. This results in four data sets, one for each race considered.

To calculate the information regarding broadband, we started with the `broadband_data_2020october.csv` data set. Only columns that were necessary were kept, and the columns were converted to the numeric class as appropriate. Each county was then classified as either “High” or “Low” depending on if their share was above or below their respective state’s median. A single county contains multiple districts, and since our data regarding the number of virtual days was based on district, the data was averaged across districts for each county. `nces_district_directory_2018.dta` provided information on which county each district belonged to, and was merged with the previous data that calculated the average number of virtual days for each district, before then calculating the average number of virtual days for each county. Finally, we average the number of virtual days for the counties labelled “High” and “Low.”

- For Abbass: for research question #2, we want to show that significant variation exists in the average number of days spent in virtual school by demographics, specifically, by race, unemployment rates, and political leanings of the area. Ignore school mode with little variation.
- For Abbass: please extend the pass rate figure by incorporating data from the replication package of the other paper, in order to stratify by race, percent in-person, FRPL and ELL (for example). You can see the figure here: <https://www.aeaweb.org/research/charts/pandemic-schooling-test-scores-us> Ignore state, probably

2.3 Features

- rigorously define variables in a neat way
- e.g., define “school closures” rigorously (e.g., a closure is identified as Tracker score of 2 or 3... what is a Tracker score?)

3 Results

Table 1: Top 5 countries by number of school closures from Jan 2020 - Dec 2021

Country	Days Closed
Azerbaijan	669
United States	667
Romania	661
Brazil	660
Panama	660

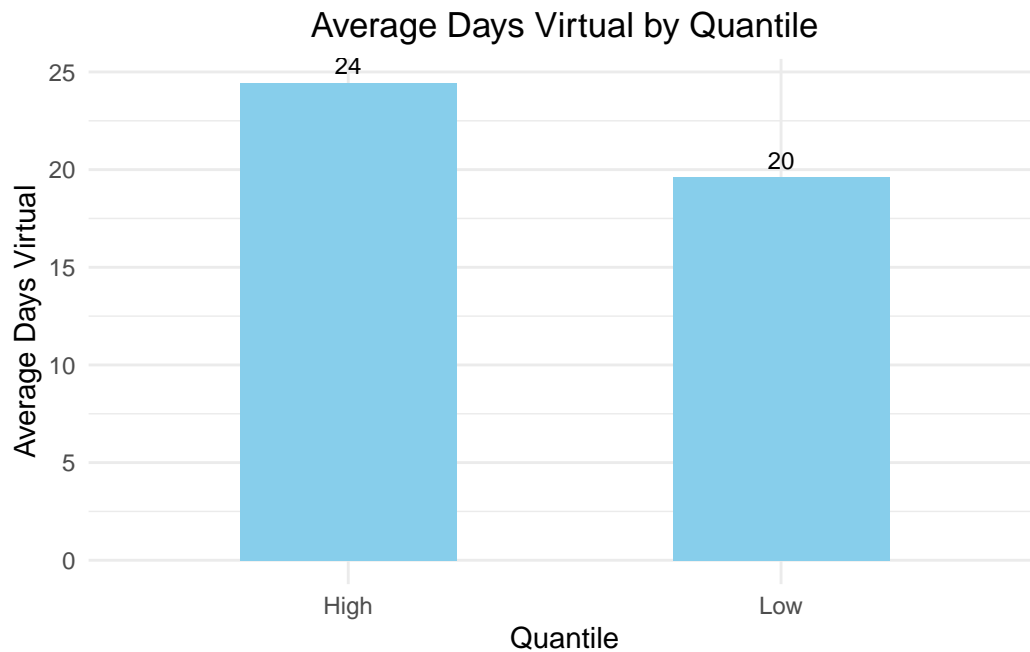


Figure 1: BroadBand

``summarise()`` has grouped output by 'year_group'. You can override using the ``groups`` argument.

4 Discussion

4.1 Findings

The analysis by Jack and Oster seeks to define the scope of COVID-19 school closures in the United States with respect to the global picture, and explore the correlation between the number of days

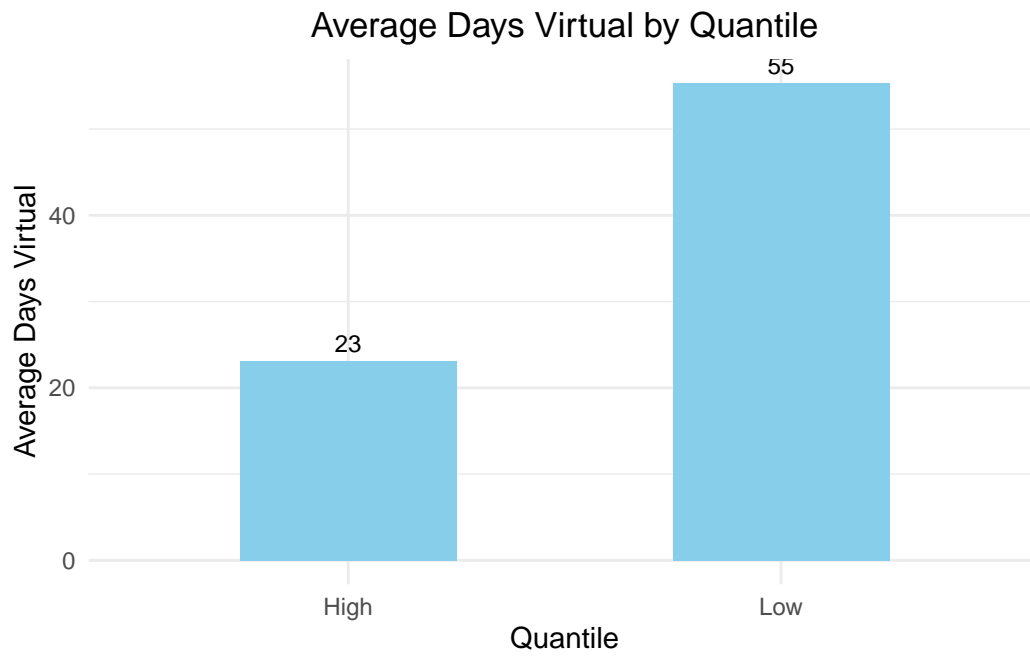


Figure 2: Share White

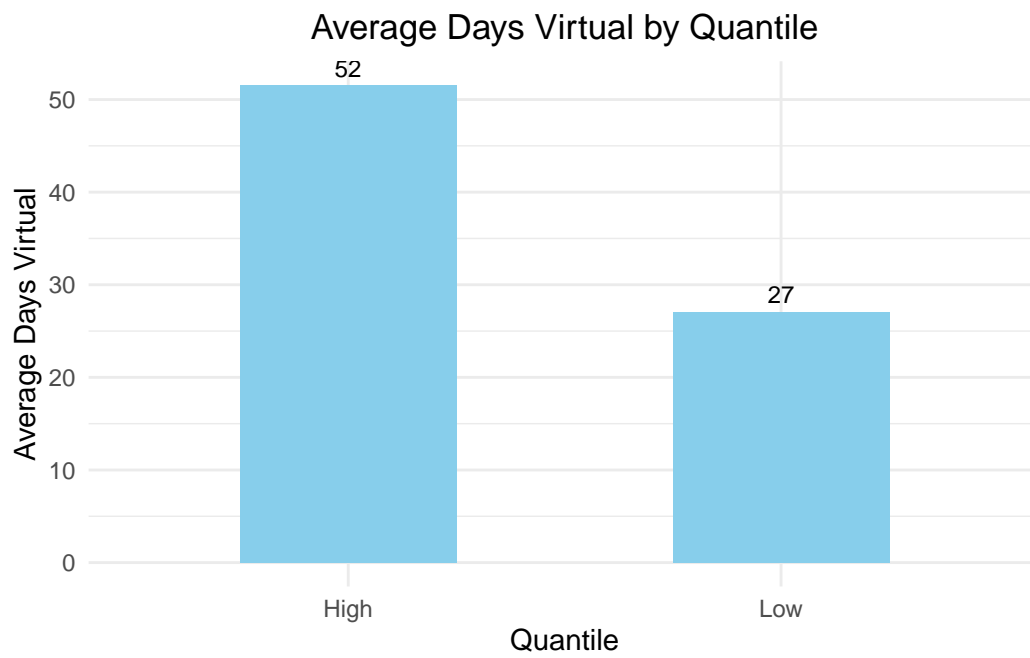


Figure 3: Share Black

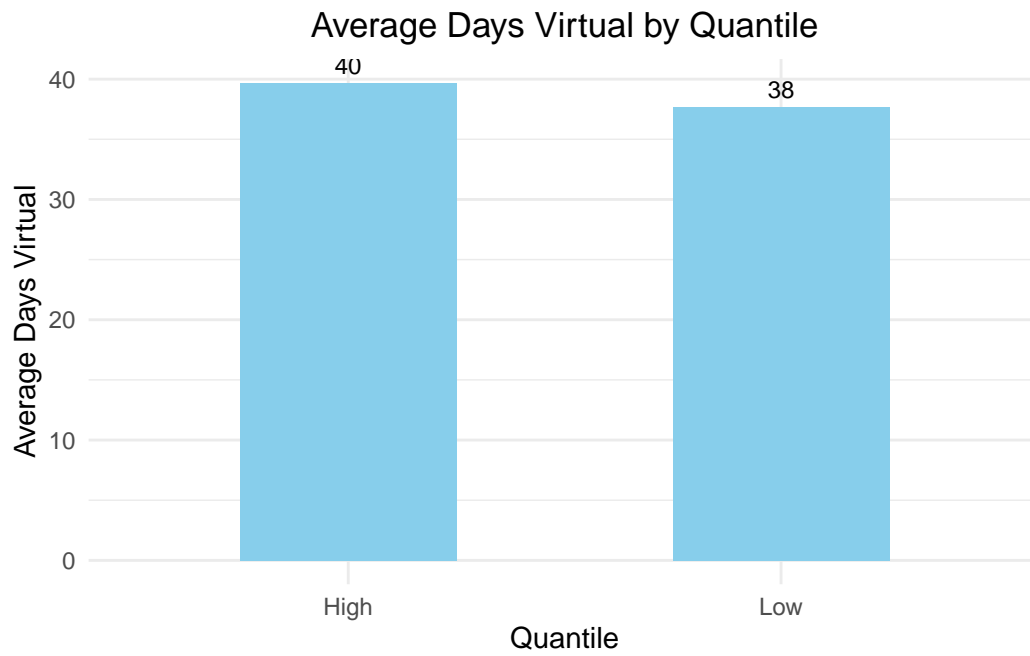


Figure 4: Share Asian

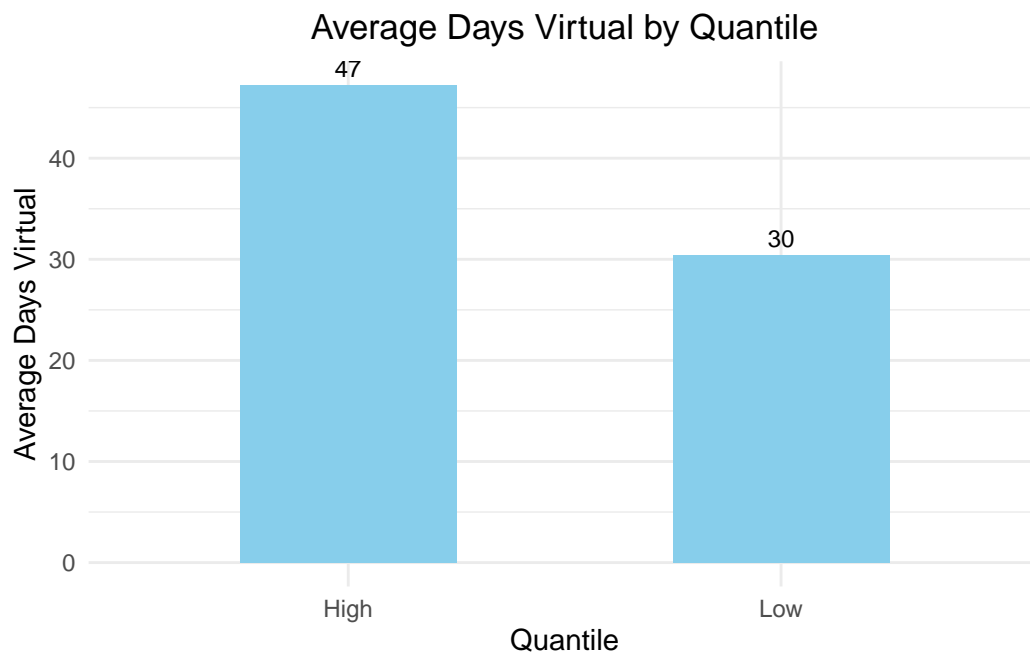


Figure 5: Share Hispanic

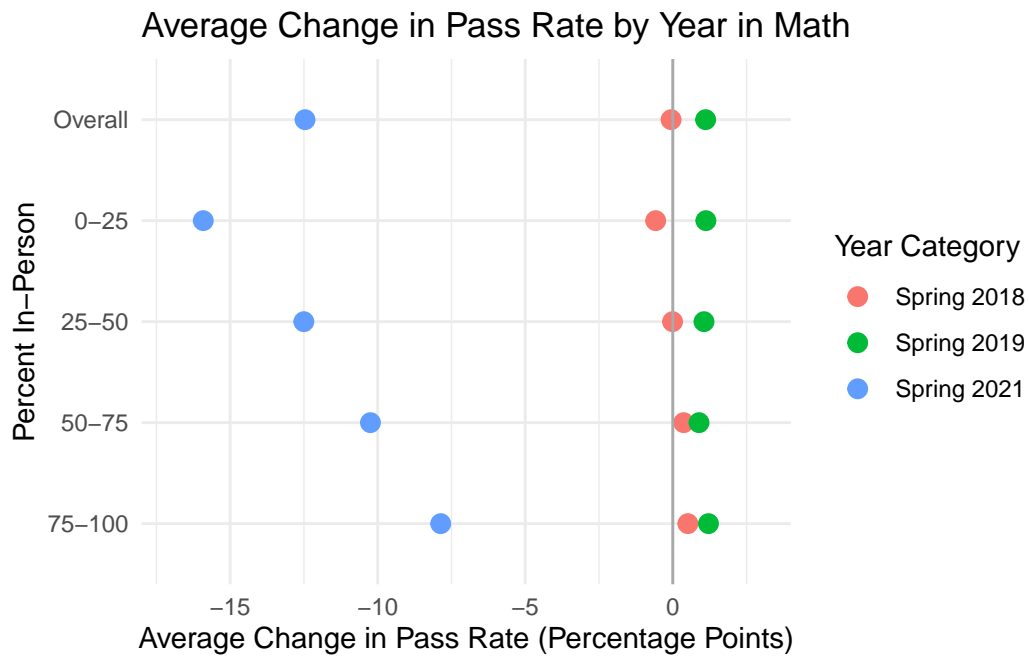


Figure 6: Test score by percent online (change)

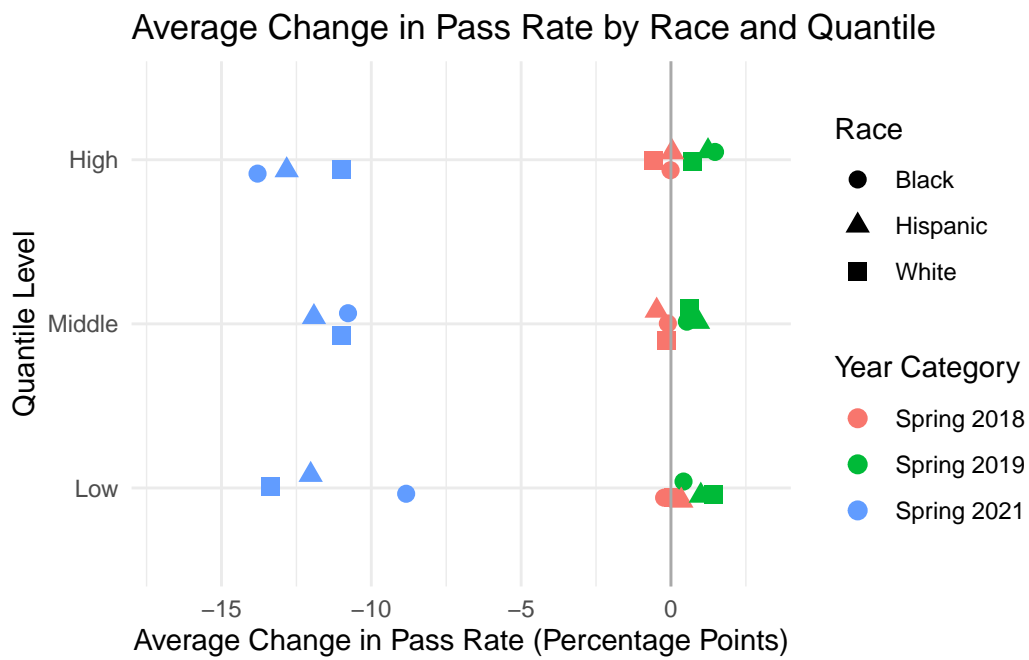


Figure 7: Update

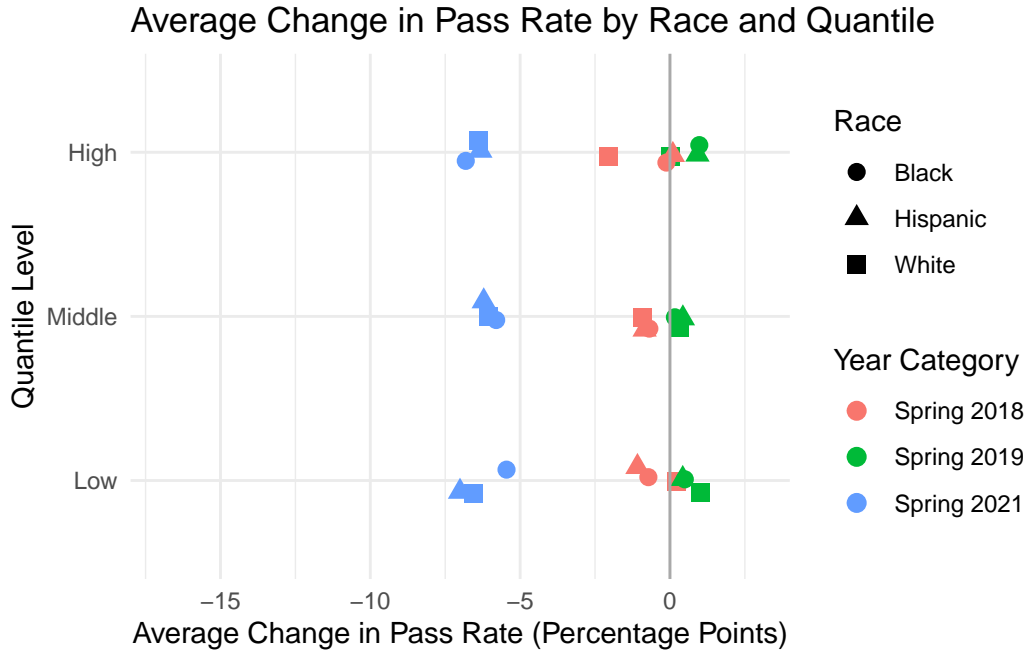


Figure 8: Update

of school closed with various demographic characteristics of 11 of its major states. The authors also compare the average change in pass rates in mathematics and ELA with the number of days of in-person schooling in Spring 2021 versus Spring 2018-2019. Our paper has successfully replicated and extended an important part of three of their major findings:

- (1) Between January 2020 and December 2021, the United States experienced the second-highest number of days of school closed worldwide, with an average of 667 days. In fact, it falls second only to Azerbaijan, which recorded an average of 669 days.
- (2) Access to in-person education was unequal by demographic characteristics. More disadvantaged districts, *i.e.*, those with higher proportions of racial minorities and lower broadband usage spent more days in virtual schooling.
- (3) During the 2020-2021 school year, students' pass rates on standardised assessments declined by 12.8 percentage points in mathematics and 6.8 in ELA. Declines were more severe in more disadvantaged districts, *i.e.*, those with higher proportions of racial minorities, ELL and FRPL students.

As noted by Jack and Oster (2023), it can be seen that the equity impacts are two-fold. First, schools (and students) with lower resources are less likely to have access to in-person instruction. Second, for such groups, the consequences of a lack of in-person instruction are more severe. This may be due to a smaller investment by such schools in effective remote learning programs or due to the challenges disadvantages students face at home, such as less reliable Internet connection or fewer community resources. Accordingly, while COVID-19 school closures imposed learning loss costs on students as a whole, they affected most negatively those who were already most vulnerable. This exacerbates the already large inequality gap.

Having replicated their work, we now turn to examine its relevance to the Netherlands. We hope to gain insights into the extent of school closures in the Netherlands and its effect on student performance, with an especial focus on students from disadvantaged homes.

4.2 Relevance to the Netherlands: a Case Study

Efforts have been made worldwide to study the impacts of school closures on student learning, typically revealing significant test-score losses (Jack and Oster 2023). The Netherlands is interesting as a “best-case” scenario for students, with a short lockdown of 8 weeks, equitable school funding and world-leading rates of broadband access (Engzell, Frey, and Verhagen 2021). According to the Organisation for Economic Cooperation and Development (OECD) (2023), the Dutch government also entered the pandemic with strong public finances, extending generous support measures for individuals and families. The Netherlands also scores close to the OECD average in school reading and places among its top performers in mathematics (Schleicher 2018). For these reasons, the Netherlands may likely provide a lower bound on student learning loss elsewhere in Europe and the world (Engzell, Frey, and Verhagen 2021).

Between January 2020 and December 2021, the Netherlands faced 55 days of school closed, considerably shorter than the global average (362 days) and the United States (677 days) (Jack and Oster 2023). Key to our discussion is that the Dutch school system provides compulsory standardised assessments in mathematics, spelling and reading twice a year: halfway into the school year in January and at the end of the school year in June. In 2020, these testing dates occurred just before and after nationwide school closures. Access to biannual test scores of 15% ($n \approx 350,000$) Dutch students between grades 4 to 7 from 2017 to 2020, published by the Student Monitoring System (LVS), thus provides a natural benchmark against which to assess learning loss. To study the data, Engzell, Frey, and Verhagen (2021) transformed these test scores into percentiles by imposing a uniform distribution separately by subject, grade and testing occasion for each of the years 2017 to 2020. In adjusting for sample composition, their results revealed a learning loss of about 3.1, 3.0 and 3.3 percentile points in mathematics, spelling and reading, respectively. The effect was equivalent to a loss of one-fifth of a school year, the same period that Dutch schools remained closed. By contrast, declines in test scores of American students between grades 3 to 8 were equivalent to a loss of about one year of learning (Binkley 2022).

The LVS also collects data on student demographics and school characteristics, as part of the national system of weighted student funding (Sanoma 2024). In comparing this data with test scores, Engzell, Frey, and Verhagen (2021) found learning losses to be up to 60% larger among students from less-educated homes, confirming the unequal costs of the pandemic on children. Moreover, they report learning losses vary considerably by school, with some schools seeing a loss of 10 percentiles or more, and some recording no loss or small gains. However, they discovered a concentration of these losses in schools with a high proportion students who are socioeconomically disadvantaged or of non-Western immigrant background. These patterns are consistent with those observed in the United States, where learning loss was also more pronounced among students of more vulnerable groups. Whether in the Netherlands or in the United States, school closures appear to have caused socioeconomic gaps to widen.

In short, despite favourable conditions, the Netherlands appeared to have made little to no progress in learning from home. However, the impact on student learning appears to be milder than that in the United States, with Dutch students losing the equivalent of one-fifth rather than a full year of learning. These findings by Engzell, Frey, and Verhagen (2021) suggest learning losses even larger in countries with weaker infrastructure or longer lockdowns. Efforts should be made to investigate the impact of school closures on learning outcomes in these countries. Moreover, to remediate consequences on student learning, social investment strategies should be designed and implemented to enhance resilience and equity in education.

4.3 Ethical Concerns

There are ethical concerns with the collection of data on racial identity, socioeconomic status and COVID-19 cases in surveys, including data sensitivity and security. Collecting personally-identifying

information (PII) may rouse feelings of anxiety and distrust, and raise important concerns about privacy and confidentiality (Ontario Human Rights Commission 2009). Individuals from vulnerable populations are particularly susceptible to such feelings of distrust in researchers (Corbie-Smith, Thomas, and St George 2002): anxiety about the research protocol, stigma, fear of disclosure, historical exploitation may be some reasons motivating a hesitancy to participate.

Moreover, stratifying test assessment scores by district-level race, ELL and FRPL shares may be problematic. The underperformance of vulnerable populations in relation to more privileged populations may reinforce discriminatory notions about their intellectual ability. These notions are harmful, having been found to impair even further the academic performance of minority groups (Steele and Aronson 1995). Indeed, Steele and Aronson (1995) have found that, when an individual is conscious of the negative stereotypes of their group, they face *stereotype threat*, becoming fearful of confirming or being judged by those stereotypes through their actions or performance. This may lead to increased self-doubt and anxiety, and thus poorer performance on assessments.

4.4 Accounting for Bias

Perhaps the most important threat to the validity of the results is the “endogeneity in schooling mode”: this is the concern that districts with more days of school closed were more affected by other pandemic-related stressors (Jack et al. 2023). For instance, more school closures in an area may arise in response to higher COVID-19 rates, and higher COVID-19 rates may in turn worsen the health and, thus, academic performance of students. The directed acyclic graph in Figure 9 demonstrates this phenomenon, whereby COVID-19 rates serve as a confounding variable, creating a possibly spurious relationship between school closures and academic performance. However, the number of school closures were shown to have very low correlation with COVID-19 rates (Jack and Oster 2023). This shows that COVID-19 rates may not be as significant of a confounding variable as initially presumed.

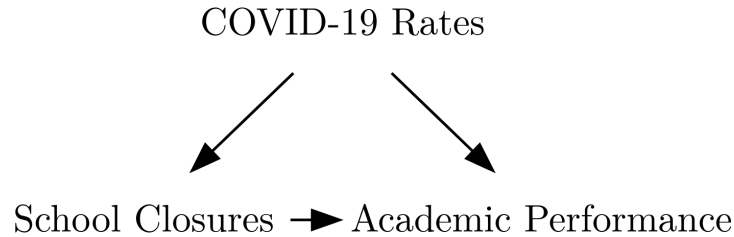


Figure 9: COVID-19 rates as a confounder, affecting the relationship between school closures and academic performance.

It is also possible that other types of lockdowns — such as the closure of counselling services or after-school activities — might have impacted student learning. This considerable difficulty of separating the effect of school closures from other pandemic-related stressors may bias the results and so affect their validity. One way in which we have helped disentangle these factors is to stratify the test assessments data by race, ELL and FRPL shares per district. By means of this “restriction” technique, we could compare test scores between more homogeneous demographic subgroups and better control for racial and demographic differences that may have impacted student learning outcomes.

Important sources of bias may have also arisen from the demographic data sets obtained from the US Department of Education’s Common Core of Data (Irwin et al. 2022), the US Bureau of Labour

Statistics (US Bureau of Labor Statistics 2021) and the US Broadband Usage Percentages data set (Kahan 2020). In particular, there are various errors that may exist in census data, collected to determine district-level race shares across the United States. These include *coverage errors*, when a respondent is missed or counted more than once, *non-response errors*, when some information about a respondent is missing, *response errors*, where a question is misunderstood or misreported by a respondent and *processing errors*, when data is incorrectly processed (“Guide to the Census of Population, 2021 / Chapter 9 – Data Quality Evaluation” 2021). On the other hand, the US Broadband Usage Percentages data set determines broadband usage by combining data from Microsoft services (Kahan 2020). In failing to account for other popular forms of internet services, such those provided by Google, Facebook, Amazon and Apple, this data set may skew the representation of broadband usage patterns in the United States.

4.5 Limitations

Being a reproduction, much of the limitations of our analysis arise from those in the original work of Jack and Oster (Jack and Oster 2023). In particular, the correlations of school closures to local demographic variables, while insightful, are not comprehensive. For instance, it would have been beneficial to determine the average number of days spent in virtual school, weighted by district enrollment, and the share of the school population that is of other ethnicities — namely, Native Americans or Alaska Natives, and Pacific Islanders — so that comparisons can be made across all important ethnic classes. Other demographic variables might include the share of students experiencing homelessness, who have limited English proficiency or who are of low socioeconomic status. Determining such correlations would more rigorously test the claim that social inequity existed in the distribution of school closures.

What is more, Jack et al.’s (2023) standardised assessments data excludes information about the corresponding broadband usage and unemployment rates by district. It instead includes data of the corresponding shares of ELL and FRPL students by district. This discrepancy prevents us from telling a full story as to how the pass rates of schools located in districts with lower broadband usage and employment rates, known to face more days of school closed than the national average, were affected. We also question whether the shares of FRPL students are a good estimator of the shares of students with low socioeconomic status. Though FRPL enrollment are widely used in education research as an indicator of student poverty, there is emerging literature that it serves as a poor proxy for poverty (Fazlul, Koedel, and Parsons 2023). In fact, using multiple data sources external to the American school system, Fazlul et al. (2023) show that FRPL rates greatly exceed what would be expected from stated income thresholds for program participation by 35 to 50%. This suggests that the shares of FRPL students per district may not be the most optimal estimator of student poverty, and that more insightful conclusions could have been obtained in examining instead, for instance, the shares of students in low-income households per district.

Lastly, the state-level assessment data is obtained from only eleven states of the United States, for which district-level data is available. This data set may not be representative of the academic performance of American students as a whole for two reasons. First, state-standardised assessments remain controversial, with critics questioning whether they accurately indicate academic ability (Yang, n.d.). Certainly, they cannot capture the ways in which students learned that were not directly given in the assessment. Second, the sample of eleven states may be too small to be generalisable. Indeed, Parolin and Kee (2021) showed that wide geographic disparities existed in school closures across the country: those concentrated on the West Coast faced declines of >75% in-person visits to schools, whereas those in the Midwest faced declines of <25%. Both of these factors put into question the validity and generalisability of the state-assessment data, and could present a valuable direction for future work.

4.6 Future Research

Reports of poor mental health (MH) in youth have been on the rise in the United States for the past decade (U.S. National Library of Medicine 2022). The COVID-19 pandemic appears to have exacerbated this trend, in significantly disrupting the lives of youth in one of their most critical periods of psycho-social development (U.S. National Library of Medicine 2022). However, the evidence on the impact of school closures — as opposed to other pandemic-related stressors — on student MH in the short- and long-term remains mixed, limited or else unknown (Jack and Oster 2023). For instance, Bacher-Hicks et al. (2022) used internet search data to track in-person bullying and cyberbullying patterns as COVID-19 shifted to remote learning in Spring 2020. Surprisingly, they reported that *both* forms of bullying dropped by 30-35%, citing transitions to virtual learning to be likely a major explanation for these trends. In contrast, Cingel et al. (2022) used online survey data, in which over 1,000 American adolescents aged 14-16 reported their classroom learning experiences and MH symptoms during the 2020-2021 school year. In this data, virtual as opposed to in-person learning was associated with reduced MH, with those online reporting less satisfaction and social connection than those in-person. In particular, problems were particularly pronounced for students identifying as transgender or gender non-conforming.

Much more research remains to understand the full impacts of the pandemic, and of school closures, in particular, on youth MH. Whilst collecting data on MH, and differentiating between the effects of school closures and other pandemic stressors on MH, are notoriously difficult, these issues remain crucial to investigate. Findings of future search will help guide policy to remediate the consequences and provide more tailored support for affected youth that promote their well-being.

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