Pandemic Schooling Mode and Student Test Scores: Evidence from U.S. School Districts *

Rebecca Jack
University of Nebraska-Lincoln

Clare Halloran
Brown University

James Okun
MIT

Emily Oster
Brown University and NBER

December 22, 2021

Abstract

We estimate the impact of district-level schooling mode (in-person versus hybrid or virtual learning) in the 2020-21 school year on standardized test scores across 11 states. Pass rates declined in 2021 compared to prior years. These declines were larger in districts with less in-person instruction. On average, passing rates in math declined by 13.0 percentage points; we estimate this decline was 15.2 percentage points smaller for districts fully in-person. Effects in English language arts showed the same pattern with smaller magnitudes. The value to in-person learning was larger for districts with larger populations of more vulnerable students.

1 Introduction

Over the course of the 2020-21 school year, students across the United States experienced educational disruptions as schools and districts grappled with how – or if – to limit in-person instruction to mitigate the transmission of Coronavirus Disease 2019 (COVID-19). Uncertainty about the role of schools in the spread of COVID-19 forced school leaders to make difficult decisions about how to appropriately support both their students and staff (McLeod and Dulsky, 2021). School districts

*We are grateful to Hannah Orlove and Molly Cook for excellent research assistance. We are grateful for comments from Jon Roth, Peter Hull, Jesse Shapiro, Josh Goodman, Andrew Bacher-Hicks, Geoffrey Kocks, and participants at seminars at University of Zurich, the University of Nebraska-Lincoln and the University of Copenhagen. The COVID-19 School Data Hub was produced with funding from Emergent Ventures at the Mercatus Center, the Chan Zuckerberg Initiative, and Arnold Ventures. Contact: Emily Oster at emily_oster@brown.edu.

thus utilized a range of schooling modes (sometimes called “learning models”) throughout the year, including school closures with virtual learning options, full-time in-person instruction, and a combination of these approaches through a “hybrid” schooling mode, which took varying forms (Kaufman and Diliberti, 2021; National Forum on Education Statistics, 2021).

In this paper, we combine data on district-level schooling modes with state test score data from 11 states. We relate the share of the school year that districts offered full-time in-person instruction (as opposed to hybrid or virtual learning) and student standardized test scores.

Our main regression specification uses a standard panel data approach, with data at the district-year level, to estimate the impact of the time spent in-person on 2021 test scores. In addition, we estimate models which isolate variation to within-state and within-commuting zone. Districts in the same commuting zone are more likely to share the same local economic conditions. As such, this latter analysis is intended to better isolate the impacts of schooling mode from other pandemic impacts (i.e. lockdowns or labor market conditions). We analyze the relationship separately across demographic splits.

We show first that access to in-person schooling varied widely across our sample, reflecting existing findings on variation in schooling mode across the U.S. (Kaufman and Diliberti, 2021). For example, districts in Virginia offered in-person instruction for an average of only 9.7 percent of the school year, compared to 88.3 percent of the school year among districts in Wyoming. In-person schooling both within and across states was more common in more politically-conservative areas, as measured by a high Republican vote share in the 2020 presidential election, and in areas with higher community COVID-19 rates. In addition, in-person schooling was more common in districts that had higher baseline test scores and a lower share of Black and Hispanic students.

Overall, there are significant declines in test scores in Spring 2021 testing relative to the last administration of state assessments in Spring 2019 (due to school closures in Spring 2020, states did not administer assessments. Therefore, Spring 2019 is the last comparable year with available data). Across all 11 states in our sample, the average decline in math is 13.0 percentage points, versus 6.5 percentage points in ELA (Table 1). These changes are well outside typical year-on-year variation. These declines vary across states, with the largest declines in Virginia (32.0 pp in math, 9.0 in ELA) and the smallest in Wyoming (4.2 math, 2.2 ELA).

Turning to our primary results, we find that test score losses are larger in districts with less in-person schooling. In our baseline analysis, with only district and year fixed effects, we estimate that offering predominantly in-person instruction rather than predominantly hybrid or virtual instruction reduces test score losses in math by 15.2 percentage points. In ELA, the loss is reduced in fully in-person settings by 5.3 percentage points. These effects are highly significant.

A key concern with these results is they may reflect other complex aspects of the pandemic or the pandemic response. Although areas with less in-person schooling also had lower COVID-19 rates, on average, they also had more non-school mitigation efforts and typically higher unemployment rates. These measures may have contributed to differences in test score outcomes (Kogan and Lavertu, 2021).

To help account for this, we repeat our analysis first controlling for time-varying demographics and unemployment rate in the area. These controls make almost no difference to the magnitude of our findings. We then run our analysis with state-year fixed effects and, finally, with both state-year and commuting zone-year fixed effects. These analyses isolate variation to relatively small areas which, in other ways, are more likely to have had similar pandemic experiences. The effects estimated within state or commuting zone are smaller (7.3 pp in math, 4.3 pp in ELA) but still highly significant. Overall, this provides additional confidence that test score outcomes are driven by variation in schooling mode.

Following the primary analysis, we estimate impacts by demographic characteristics. We estimate effects separately by characteristic, by splitting the sample into two groups at the median share for each of four demographic variables: Black students, Hispanic students, students who are eligible for free and reduced price lunch (FRPL), and English language learners (ELL). For each characteristic, we find that the impact of in-person schooling on math scores is larger in districts with higher shares. We also find that the impact of in-person schooling on ELA scores is larger in districts with higher shares of Black students and in districts with higher shares of FRPL.

Overall, these splits suggests traditionally underserved student groups benefited the most academically from access to in-person instruction. However, we also find that districts with greater shares of students in these groups were *less likely* to have access to in-person schooling. This leads us to the troubling finding that students who are Black, Hispanic, or lower-income have been doubly impacted by the pandemic: Compared to their white and higher-income peers, they experienced greater learning losses as a result of non-in-person instruction *and* – to compound these losses – they spent more time out of school than their peers as well.

We perform a number of robustness checks. First, we show the effects are similar across grades. Second, we provide some bounding analysis on the effects we estimate using variation in test participation. Test participation rates were lower in Spring 2021 as compared to prior years, and these differences are larger in districts with less in-person schooling. Some reports indicate that lost participation seems to be larger among groups that traditionally perform more poorly in testing (e.g., ELL or students receiving special education services).[1] This would suggest our estimates are biased downwards. However, we show that even if we assume *all* of the non-participants would have passed the test, our impacts in math remain (impacts in ELA would be eliminated by this bound).

Finally, we use 9 states which report multiple proficiency levels to estimate whether the effects we observe appear at other parts of the score distribution. We find that they do: The share of students testing at the lowest proficiency level declines with greater in-person schooling and those testing at the highest proficiency level increases.

Our paper contributes to a number of strands of literature. First, we add to the research about the characteristics of schooling modes in the U.S. in the 2020-21 school year (Kurmann and Lalé, 2021; Fuchs-Schündeln, 2021). Kurmann and Lalé (2021) used a combination of Safegraph cell phone data on foot-traffic and information on schooling modes to investigate differences in in-person learning by school type (private vs. public), region, and school characteristics. Fuchs-Schündeln and colleagues (2021) similarly utilize data from SafeGraph to explore differences in schooling mode by schooling levels (elementary vs. secondary) and school type. We expand on this by using comprehensive state data to investigate differences across states and also to better understand differences across demographic characteristics.

More broadly, we add to the literature on how students' time out of school impacts their academic achievement (McCombs et al., 2011; Alexander et al., 2016; von Hippel, Workman, and Downey, 2018). In their synthesis of the research on summer learning loss, McCombs and colleagues (2011) conclude that while all students experience summer learning loss, on average, this is particularly true for low-income students, and that losses accumulate over time. Other research has focused on learning loss resulting from unplanned school closures or disruptions due to events such as weather emergencies (Pane et al., 2008; Sacerdote, 2012; Lamb et al., 2013; Harmey and Moss, 2021). These studies generally find disrupted schooling is most harmful for students and schools which have fewer resources before the disruption.

More specifically, we contribute to the small but growing literature on the impacts of COVID-19 schooling disruptions on students, which includes, for example, impacts on aspects of students'

1. See, e.g., Colorado Department of Education, 2021; Ohio Department of Education, 2021; Rhode Island Department of Education, 2021

health (Bacher-Hicks et al., 2021; ED, 2021b, Verlenden et al., 2021) and impacts on public school enrollment (Dee et al., 2021; Musaddiq et al., 2021). With regard to pandemic impacts on academic achievement, initial research provided *projections* of potential learning loss (Kuhfeld and Tarasawa, 2020; Wyse et al., 2020), with estimates that impacts would be hardest on our nation's most vulnerable students (Dorn et al., 2020; Kuhfeld et al., 2020; Azevedo et al., 2021). Other research has relied on parent or teacher perspectives of students outcomes based on reported schooling mode (Chen et al., 2021; Verlenden et al., 2021).

Of note are several papers which use test scores to directly study impacts of Spring 2020 closures on learning, largely in Europe (Contini et al., 2021; Engzell et al., 2021; Maldonado and De Witte, 2021; Schult et al., 2021; Tomasik et al., 2021), but also South Africa (Ardington et al., 2021). On the whole, these studies focus on elementary student outcomes, and each found evidence of learning loss as a result of Spring 2020 school closures. In addition, one study in the U.S. used assessment data in Grades 4–10 among a sample of California school districts between Fall 2019 and Fall 2020 and concluded that students experienced learning loss in both math and ELA, particularly in Grades 4–7 (Pier et al., 2021). Meanwhile, Lewis and colleagues (2021) compare overall student learning during the pandemic to pre-pandemic years, but without reference to schooling mode.

Taken together, despite differences across countries, age groups, and subject areas, systematic reviews of the literature tend to find learning losses as a result of limited in-person schooling access (Hammerstein et al., 2021; Storey and Zhang, 2021; West and Lake, 2021). To date, however, little is known about how U.S. student academic outcomes vary by state-reported schooling mode during the 2020-21 school year.

From a policy standpoint, our results highlight the non-health implications of the pandemic, which may be long-lasting. There is significant funding at both the federal and state levels to address these issues; our findings suggest the possibility of targeting certain districts and students in these efforts. These data also highlight the value of in-person learning and may provide a caution when considering school closures in the future.

2 Data

Our analyses use three sources of data: 1) district-level schooling mode data from the 2020-21 school year; 2) district-level test score data from Spring 2016–2019 and 2021; and (3) district demographic data from NCES. We explain these data sources below.

2.1 Schooling Mode Data

District-level schooling mode data are drawn from the COVID-19 School Data Hub (CSDH). This is a public database, produced by our research team, which uses state-sourced data to document the schooling modes used by school districts during the 2020-21 school year.

The CSDH sources raw data from State Education Agencies (SEAs) on schooling modes across schools or districts over the 2020-21 school year.[2] The CSDH reviewed all data from SEAs and either used each state's learning model classification or, if more than three categories were provided, collapsed the models into the following three categories for each time period (typically weekly or monthly): 1) "in-person" (all or most students had access to traditional, 5-day-per-week, in-person instruction); 2) "virtual" (all or most students received instruction online, five days a week); and 3) "hybrid" (schooling modes that did not fall into one of these approaches).[3] Finally, for the purpose of our analysis, each district was classified according to one of these schooling modes based on their *predominant* approach during the 2020-21 school year. Thus, results we report here for districts that were fully in-person are districts that offered in-person instruction for the majority of the school year.

We included states in our analyses if the state provided learning model data at monthly, biweekly, or weekly intervals during the 2020-21 school year. When schooling mode was available at the district level only, we used this mode in our analyses. In cases where schooling mode was available at the school or district-grade-band level (e.g., elementary, middle, or high), we weighed the elementary and middle schooling modes equally to reflect the test score data which is restricted to third through eighth grade. Finally, we calculated the average percent of the school year that each district offered each schooling mode using every time period's classification and the length of that time period. We did not include the week of Thanksgiving 2020 and the last two weeks of December 2020 in this calculation even when districts reported a schooling mode for those weeks.

Our resulting data file is at the district level. The calculated shares by schooling mode represent our best attempt at capturing the amount of time students were offered in-person, hybrid, and virtual instruction in a particular district. However, changes occurred on a daily basis throughout the year at the district, school, and classroom level due to county-level COVID-19 case rates, state- and district-level quarantine procedures, and parental or community input.

2. The CSDH also contains data on student enrollment by schooling mode, if available from State Education Agencies. We do not use those data here.

3. More details about the data construction in each state are available from the CSDH at https://www.covidschooldatahub.com/

2.2 Test Score Data

We draw test score data from state-level testing in Spring 2021. We included states in the analysis if they met the following test score criteria: 1) at least two years of pre-pandemic test data were available; and 2) no significant testing changes occurred over this period, which would have prohibited comparisons. We additionally excluded Alaska, Nevada, and New York due to low participation rates in state testing in Spring 2021 (approximately 64% overall in Alaska, 40% overall in New York, and 61% overall in Nevada).

We focus on test scores for Grades 3–8 in ELA and math. Our primary outcomes are subject-area pass rates, which measure the share of students who score proficient or above in ELA or math on state assessments. When possible, we will consider test scores by grade and consider higher and lower score cutoffs. We draw from district-level participation data across all states to show robustness to variation in participation. We present each state's testing details in Appendix B.

Our final sample includes 11 states: Colorado, Connecticut, Massachusetts, Minnesota, Mississippi, Ohio, Rhode Island, Virginia, West Virginia, Wisconsin and Wyoming. Several states have also reported learning losses using these raw data (Colorado Department of Education, 2021; Connecticut State Department of Education, 2021; Ohio Department of Education, 2021).

2.3 Additional Data Sources

In addition to these primary data sources, we draw information on school demographics from the National Center for Education Statistics (NCES). These data include district-level information on the share of enrolled students by race and ethnicity as well as the share of students who are eligible for free and reduced price lunch (FRPL) and the share of students who are English language learners (ELL). NCES also provides enrollment data; we use 2019-20 enrollment data for the 2020-21 school year as it is the most recent available. To capture the possible role of variation in COVID-19 case rates in driving district opening decisions, we use district-level COVID-19 case counts from USA Facts.[4] We focus on the average level of COVID-19 cases per 1,000 people over the school year in the central zip code of the school district.

Finally, we use data on the Republican vote share in the 2020 presidential election, commuting zone data from the U.S. Census and monthly county-level unemployment data from the Bureau of Labor Statistics averaged by school year from June-May for 2016-2021.

4. Available at https://usafacts.org/.

3 Results

3.1 Summary Statistics, Pass Rate Changes and Demographics

In Table 1, we present summary statistics by state. Panel A focuses on schooling mode and demographics. Of the states in our analyses, in-person learning rates are highest in Wyoming (88.3%) and Mississippi (66.9%), and lowest in Minnesota (16.2%) and Virginia (9.7%). Conversely, Virginia and Colorado have the highest share of district time spent in fully virtual learning (38.6% and 29.2%, respectively). States in the sample vary across demographic characteristics as well, including their share of students who are Black and Hispanic, eligible for free and reduced price lunch programs, and those who are English language learners (ELL).

In Appendix Table A.1, we illustrate the pairwise correlations between the demographic and pandemic variables and in-person learning. We observe more in-person learning in districts with higher baseline test scores, fewer Black and Hispanic students, and smaller populations of students who are ELL or FRPL-eligible. In contrast, the overall picture suggests that districts with more historically underserved students – more students of color, more lower-income students, or more ELL students – were less likely to have access to in-person schooling.

In Appendix Table A.1, we also show that districts with a greater Republican vote share in 2020 were also more likely to have in-person learning than counterparts with lower Republican vote shares. In addition, districts with higher COVID-19 rates showed greater in-person schooling. Much has been written on the possible role of schools in driving COVID-19 cases, most of which suggests schools were not significant drivers of COVID-19 (UNICEF, 2020, Goldhaber et al., 2021; Harris et al., 2021). The positive correlation here likely reflects differences in other pandemic restrictions which were correlated with schooling mode choice and influenced COVID-19 rates.

In Panel B of Table 1, we illustrate changes in pass rates in math and ELA between Spring 2019 and Spring 2021 (tests were not given in any state in the Spring of 2020 due to school closures at the onset of the pandemic in the U.S.). This table also provides a range of year-on-year changes in the pre-pandemic period. We find that enrollment-weighted average pass rates declined by 13.0 percentage points between 2019 and 2021 in math, and 6.5 in ELA. In both math and ELA, the largest declines were seen in Virginia (32.0 and 9.0 percentage points, respectively), with the smallest declines in Wyoming (4.2 and 2.2 percentage points, respectively). The changes in pass rates for math are considerably larger than the changes in scores for ELA. This is consistent with NWEA's finding that students experienced greater test score declines in math as compared to ELA in Spring 2021 (Lewis et al., 2021) and matches a larger literature which shows math scores are more responsive to schooling differences (Betts and Tang, 2011; Angrist et al., 2013).

3.2 Schooling Mode and Test Score Changes

We turn now to estimating the impact of the pandemic schooling mode on student test scores. Our primary treatment is the share of the school year that districts offered full-time in-person learning options, which is compared with the share of the school year that districts offered either hybrid or fully virtual schooling. Effectively, we can view these analyses as identifying the possible losses as a result of deviating from a traditional school schedule, characterized by in-person learning.

We begin by illustrating the relationship between schooling mode and changes in pass rates graphically. Figure 1 shows average year-on-year changes in test scores across districts which are binned into 12 groups by the share of in-person schooling. This share ranges from districts which had 0% of their school year in-person to those offering traditional in-person instruction 100% of the time. In this figure, the triangles indicate the changes between 2019 and 2021, over the pandemic year. The circles show year-on-year changes for those same districts pre-pandemic, from 2017-2019.

In Figure 1, we show these results separately for math (Panel A) and ELA (Panel B). In both cases, we see a positive relationship between test score changes and the extent to which districts offered fully in-person instruction. Although there are clear declines in tests scores in all bins, these declines are smaller in districts with more in-person schooling. There is little variation in test score changes across district groups in the pre-pandemic period; this suggests the variation in test scores losses does not reflect pre-existing trends.

We turn now to regressions. Our approach is to estimate a standard panel regression at the district-year level. The independent variable of interest is the in-person share; the outcome is the average pass rate in math or ELA over Grades 3–8. All regressions include district and year fixed effects and standard errors are clustered by district. We present our results in Table 2 for math (Panel A) and ELA (Panel B). In Column (1), we show baseline regressions which include only the fixed effects as controls. These regressions suggest that moving a district from 0% to 100% access to in-person learning would have reduced test score loss during the pandemic year by 15.2 percentage points in math and 5.3 percentage points in ELA. Both are highly significant.

A key concern with this analysis is that the results may be driven by other differences across areas in the pandemic experience. This could include differences in COVID-19 rates or political leanings, for example. Perhaps most relevant is that areas with greater school closures may also have seen more lockdowns in general, and more labor market disruptions. To the extent that adult unemployment affects student school performance (Kogan and Lavertu, 2021), this could drive part of the impacts we observe.

To address this concern, we add a number of controls in Columns (2) - (4) of Table 2. First, Column (2) includes time-varying demographic controls: the share of students by race, FRPL and ELL status. This column also includes the unemployment rate in the county. The coefficients for both math and ELA are very similar, if slightly larger than the baseline results in Column (1).

Columns (3) and (4) include location-year fixed effects, where the location is either the state (Column (3)) or state and commuting zone (Column (4)). Including these controls isolates the variation we are using to smaller geographic areas with likely much more similar experiences in the pandemic overall.

The effect sizes in Columns (3) and (4) are smaller in math, and comparable in ELA. In both cases, the effects remain highly significant. This increases our confidence that these effects reflect variation in schooling mode. As a corollary to these results, we show the estimated impact of in-person learning by state in Appendix Figure A.1. The positive effect of in-person learning shows up in most states in the sample.

Schooling mode was not random and it is difficult to fully rule out all possible confounds. However, these analyses give us additional confidence that the effects we see on test scores are primarily driven by school experience.

In our primary analysis, our focus is on in-person learning, with the omitted category being a combination of hybrid and virtual learning. Appendix Table A.2 replicates Column (2) of Table 2 including both in-person and hybrid learning shares; the omitted category is virtual learning. We observe an intermediate coefficient on hybrid learning share, consistent with the fact that hybrid districts had an intermediate amount of school time.

Demographic Variation

To explore demographic variation in the effect of in-person learning, we divide the sample of districts into two groups at the median based on shares by race and ethnicity, FRPL-eligibility, and ELL status and estimate effects separately by group. We focus on the specification in Column (2) of Table 2.

The results are shown in Figure 2. In all cases, districts with a larger share of historically underserved students show larger impacts. This is especially true across student subgroups by race and ethnicity. Districts with a higher share of Black or Hispanic students show effects of in-person learning which are about twice as large as districts with a lower share.

This finding amplifies the disparate impact of the pandemic schooling disruptions on students of color. Districts with more students in these groups were less likely to have access to in-person schooling in the first place; thus, even if the impact of less access to in-person instruction were the same across districts, historically underserved students would be more impacted overall. The finding here shows these districts had the largest impact of the alterations in schooling mode.

3.3 Robustness

We consider three main robustness checks. First, we look at the effects by grade. Second, we create bounds based on variation in participation rates. Third, we estimate impacts for different proficiency levels. In all cases we use our primary specification, shown in Column (2) of Table 2.

Effects by Grade

In Panel A of Table 3, we provide estimates of the impact of in-person learning by grade. This is relevant for two reasons. First, we may be interested in whether there are variations in the value of in-person learning by age group. Second, to the extent that there are changes in the size of these grades as a result of pandemic, it is possible that these changes could be driving the overall impact (this would be a form of Simpson's Paradox).

The estimated effect of in-person learning is positive and significant in all grades in both subjects. There are no especially striking trends; the largest impact in math is seen in Grade 8, and the largest impact in ELA is seen in Grade 5. In general, however, the magnitudes are very similar across all grades in both subjects.

Participation

A second robustness issue relates to participation rates. Broadly, the concern is that lower testing participation rates in 2021 – both overall, and in non-in-person districts in particular – could drive our results. There are two more specific issues.

First, some students may simply have left the U.S. public school system and, therefore, do not appear in the testing pool at all. If this were a large group, and if it were disproportionately made up of students with more resources, this could impact the test scores. In practice, however, Dee and colleagues (2021) show that drops in enrollment primarily affected kindergarten. The difference in student departures from public school enrollment due to virtual instruction was only around 1 percentage point across elementary grades (Grades 1–5), with inconsistent results across middle school grades (Grades 6–8) . Even if all students who left the public school system would have received passing scores, this would not have greatly altered district-level test score outcomes.

The second issue is that many states experienced lower test participation rates in the 2020-21 school year as compared to previous years. Prior to the pandemic, the U.S. Department of Education (ED) required at least 95 percent of students in each state – and 95 of students in each subgroup – to participate in state assessments for accountability purposes. In Spring 2021, however, ED waived this requirement, stating that "some schools and districts may not be able to safely administer statewide summative assessments this spring using their standard practices, while others may wish to prioritize learning time during the scant in-person schooling time this year in many communities" (ED, 2021a). The CRPE found that just half of the states with available 2021 assessment results as of November 2021 had overall participation rates over 90 percent. We observe that the 2021 participation rate drops are typically larger in districts with more virtual learning. One interpretation of both lower pass rates overall and the differences by mode is that they are driven by these participation changes.

Our baseline estimates will be accurate for the overall population if test takers are drawn randomly from the population. If those who opt in to the test are likely to perform *better*, then our estimates will understate the losses. If those who opt in are likely to perform worse, then our estimates will overstate them.

Based on state reports, participation declines during the pandemic appear to be larger among historically underserved student groups, such as students of color, students of lower socioeconomic status (SES) backgrounds, and students receiving special education services, among other student subgroups (Colorado Department of Education, 2021; Ohio Department of Education, 2021; Rhode Island Department of Education, 2021). Participation among ELLs also declined nationally by approximately 30 percentage points (Najarro, 2021). Assessment scores for these students typically lag behind other student subgroups, such as their white peers, higher-SES students, students who are not receiving special education services, or students who are English proficient (ED, 2021b). Thus, to the extent that these subgroups had lower participation rates in 2021 compared to prior years, our estimates will understate test score losses.

To evaluate this issue more formally, we create bounds using district-level participation rates. For one bound, we assume all students who did not take the test would have passed. For the other, we assume none of them would have passed. We show the estimates with these bounds in Panel B of Table 3. The first row shows our main estimated effects. The second row shows the bound under the assumption that all non-takers would have passed. The third shows the bound under the assumption they would have failed.

For math, both bounds suggest in-person learning was beneficial. For ELA we observe that the effect would be reversed if all the non-testing students had passed. In both cases, the effects are considerably larger under the other bound.

Given the background evidence that the test score drops were larger among students from more historically underserved populations, it seems possible that the participation drops actually bias our effects downward. The result shows that even under the opposite assumption, there would still be large losses in math.

3.3.1 Other Test Score Levels

Our primary outcome is pass rates, defined as the share of students who receive a score which the state defines as sufficient to indicate mastery of that grade level material. One concern about this binary outcome is that it may be less responsive to learning changes in some districts than others. In a high-performing district where nearly all students perform well above the pass rate level, declines in learning may not reflect in this "pass" outcome. To the extent that these higher-performing districts are more likely to have in-person learning, this could bias the results.

As a final robustness check, therefore, we estimate the impact on two other metrics. The first is the share of students in the lowest category (as defined by each state); the second is the share of students in the highest category. In general, states typically have four categories, with passing scores defined as being in one of the top two groups. We have these measures for nine states in our sample: Colorado, Connecticut, Massachusetts, Minnesota, Mississippi, Rhode Island, Wisconsin, West Virginia, and Wyoming. By examining the lowest and highest categories, we are able to see whether there are impacts of schooling mode on the lower and higher performing parts of the distribution.

In Panel C of Table 3, we show the impact on these two other outcomes. We observe that in-person learning matters for both of these outcome measures. A greater share of time in-person reduces the share of students in the lowest pass rate group, and raises the share in the highest group. This suggests that in-person learning matters across the distribution.

4 Conclusion

This paper analyzes the relationship between in-person schooling mode and test score changes during the COVID-19 pandemic of the 2020-21 school year. Overall, we find considerable declines in test scores during the 2020-21 school year, and these declines were larger in school districts with less in-person instruction.

Although student test scores across all states in our sample were affected by the COVID-19 pandemic, our results show significant inequality in outcomes. Students in districts with less in-person learning had greater test score declines, and these districts were more likely to serve larger populations of students who are Black, Hispanic, English language learners, or eligible for free and reduced price lunch. Districts with students of color and lower income students were not only more likely to have only virtual schooling options, but also showed larger treatment effects. The net impact is a potentially significant increase in learning inequality.

Test scores are only one measure of student learning during the 2020-21 school year. This paper cannot capture ways that students learned that were not reflected on such assessments; we also cannot account for pandemic-related changes in students' lives beyond schooling mode. However, these results can serve as a starting point for education leaders and policymakers as they weigh where to target funding moving forward in order to support student learning. Specifically, our analyses suggest that a focus on areas which had less in-person learning over the 2020-21 school year would be critical. More generally, our analyses demonstrate that hybrid or virtual schooling modes cannot support student learning in the same way as fully in-person instruction can. As such, educational impacts of schooling mode on students' learning outcomes should be a critical factor in policy responses to future pandemics or other large-scale schooling disruptions.

References

Alexander, Karl, Sarah Pitcock, and Matthew C Boulay. 2016. *The summer slide: What we know and can do about summer learning loss.* Teachers College Press.

Angrist, Joshua D, Parag A Pathak, and Christopher R Walters. 2013. "Explaining charter school effectiveness". *American Economic Journal: Applied Economics* 5 (4): 1–27.

Ardington, Cally, Gabrielle Wills, and Janeli Kotze. 2021. "COVID-19 learning losses: Early grade reading in South Africa". Elsevier, *International Journal of Educational Development* 86:102480.

Azevedo, João Pedro, Amer Hasan, Diana Goldemberg, Koen Geven, and Syedah Aroob Iqbal. 2021. "Simulating the potential impacts of COVID-19 school closures on schooling and learning outcomes: A set of global estimates". Oxford University Press, *The World Bank Research Observer* 36 (1): 1–40.

Bacher-Hicks, Andrew, Joshua Goodman, and Christine Mulhern. 2021. "Inequality in household adaptation to schooling shocks: Covid-induced online learning engagement in real time". Elsevier, *Journal of Public Economics* 193:104345.

Betts, Julian R, and Y Emily Tang. 2011. "The Effect of Charter Schools on Student Achievement: A Meta-Analysis of the Literature." ERIC, *Center on Reinventing Public Education.*

Center on Reinventing Public Education (CRPE). 2021, November. *CRPE 2021 State Response Database.* CRPE.

Chen, Li-Kai, Emma Dorn, Jimmy Sarakatsannis, and Anna Wiesinger. 2021. *Teacher survey: Learning loss is global—and significant.* McKinsey & Company.

Colorado Department of Education. August 2021. *News release - statewide assessment results show decreased participation, lower CMAS scores than previous years.* Technical report. Colorado Department of Education.

Connecticut State Department of Education. August 2021. *Statewide Summative Assessment Report 2020-21.* Technical report. Connecticut State Department of Education.

Contini, Dalit, Maria Laura Di Tommaso, Caterina Muratori, Daniela Piazzalunga, and Lucia Schiavon. 2021. *The COVID-19 pandemic and school closure: learning loss in mathematics in primary education.* Technical report. Collegio Carlo Alberto.

Dee, Thomas, Elizabeth Huffaker, Cheryl Phillips, and Eric Sagara. 2021. *The revealed preferences for school reopening: Evidence from public-school disenrollment.* Technical report. National Bureau of Economic Research.

Dorn, Emma, Bryan Hancock, Jimmy Sarakatsannis, and Ellen Viruleg. 2020. *COVID-19 and learning loss—disparities grow and students need help.* McKinsey & Company.

Engzell, Per, Arun Frey, and Mark D Verhagen. 2021. "Learning loss due to school closures during the COVID-19 pandemic". National Acad Sciences, *Proceedings of the National Academy of Sciences* 118 (17).

Fuchs-Schündeln, Nicola, Dirk Krueger, Andre Kurmann, Etienne Lale, Alexander Ludwig, and Irina Popova. 2021. *The Fiscal and Welfare Effects of Policy Responses to the Covid-19 School Closures.* Technical report. National Bureau of Economic Research.

Goldhaber, Dan, Scott A Imberman, Katharine O Strunk, Bryant Hopkins, Nate Brown, Erica Harbatkin, and Tara Kilbride. 2021. *To what extent does in-person schooling contribute to the spread of COVID-19? Evidence from Michigan and Washington.* Technical report. National Bureau of Economic Research.

Hammerstein, Svenja, Christoph König, Thomas Dreisörner, and Andreas Frey. 2021. "Effects of COVID-19-Related School Closures on Student Achievement—A Systematic Review". PsyArXiv.

Harmey, Sinéad, and Gemma Moss. 2021. "Learning disruption or learning loss: using evidence from unplanned closures to inform returning to school after COVID-19". Taylor & Francis, *Educational Review,* 1–20.

Harris, Douglas N, Engy Ziedan, and Susan Hassig. 2021. *The Effects of School Reopenings on COVID-19 Hospitalizations.* National Center for Research on Education Access and Choice.

Kaufman, Julia H, and Melissa Kay Diliberti. 2021. *Divergent and Inequitable Teaching and Learning Pathways during (and Perhaps Beyond) the Pandemic: Key Findings from the American Educator Panels Spring 2021 COVID-19 Surveys.* RAND Corporation.

Kuhfeld, Megan, James Soland, Beth Tarasawa, Angela Johnson, Erik Ruzek, and Jing Liu. 2020. "Projecting the Potential Impact of COVID-19 School Closures on Academic Achievement". SAGE Publications Sage CA, *Educational Researcher* 49 (8): 549–565.

Kuhfield, Megan, and Beth Tarasawa. 2020. *The COVID-19 Slide: What Summer Learning Loss Can Tell Us about the Potential Impact of School Closures on Student Academic Achievement. Brief.* NWEA.

Lamb, John, Sarah Gross, and Mark Lewis. 2013. "The Hurricane Katrina Effect on Mathematics Achievement in Mississippi". *School Science and Mathematics* 113 (2): 80–93.

Lewis, K, M Kuhfeld, E Ruzek, and Andrew McEachin. 2021. *Learning During COVID-19: Reading and Math Achievement in the 2020-21 School Year.* NWEA.

Maldonado, Joana Elisa, and Kristof De Witte. 2021. "The Effect of School Closures on Standardised Student Test Outcomes". Wiley Online Library, *British Educational Research Journal.*

Marcotte, Dave E, and Steven W Hemelt. 2008. "Unscheduled School Closings and Student Performance". *Education Finance and Policy* 3 (3): 316–338.

McCombs, Jennifer Sloan, Catherine H Augustine, and Heather L Schwartz. 2011. "Making Summer Count: How Summer Programs Can Boost Children's Learning". RAND Corporation.

McLeod, Scott, and Shelley Dulsky. 2021. "Resilience, Reorientation, and Reinvention: School Leadership During the Early Months of the COVID-19 Pandemic". In *Frontiers in Education,* 6:70. Frontiers.

Musaddiq, Tareena, Kevin M Stange, Andrew Bacher-Hicks, and Joshua Goodman. 2021. *The Pandemic's Effect on Demand for Public Schools, Homeschooling, and Private Schools.* Technical report. National Bureau of Economic Research.

National Forum on Education Statistics. 2021. *Forum Guide to Attendance, Participation, and Engagement Data in Virtual and Hybrid Learning Models (NFES 2021–058).* Technical report. National Forum on Education Statistics, US Department of Education. Washington, DC: National Center for Education Statistics.

Ohio Department of Education. September 2021. *Data Insights: Evidence of the Pandemic's Impact on Students in 2020-2021.* Technical report. Ohio Department of Education.

Pane, John F, Daniel F McCaffrey, Nidhi Kalra, and Annie J Zhou. 2008. "Effects of Student Displacement in Louisiana During the First Academic Year After the Hurricanes of 2005". *Journal of Education for Students Placed at Risk* 13 (2-3): 168–211.

Pier, Libby, Heather Hough, Michael Christian, Noah Bookman, Britt Wilkenfeld, and Rick Miller. 2021. *COVID-19 and the Educational Equity Crisis: Evidence on Learning Loss From the CORE Data Collaborative.* Policy Analysis for California Education.

Rhode Island Department of Education. 2021. *English Language Arts and Mathematics Assessment Results 2021.* Technical report. Rhode Island Department of Education.

Schult, Johannes, Nicole Mahler, Benjamin Fauth, and Marlit Annalena Lindner. 2021. "Did Students Learn Less During the COVID-19 Pandemic? Reading and Mathematics Competencies Before and After the First Pandemic Wave". PsyArXiv.

Storey, Nathan, and Qiyang Zhang. 2021. "A Meta-analysis of COVID Learning Loss". EdArXiv.

Tomasik, Martin J, Laura A Helbling, and Urs Moser. 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". Wiley Online Library, *International Journal of Psychology* 56 (4): 566–576.

U.S. Department of Education. 2021b. *Education in a Pandemic: The Disparate Impacts of COVID-19 on America's Students.* U.S. Department of Education.

———. 2021a. *U.S. Department of Education Releases Guidance to States on Assessing Student Learning During the Pandemic.* U.S. Department of Education.

UNICEF. 2020. *In-Person Schooling and COVID-19 Transmission: A Review of the Evidence.* UNICEF.

Verlenden, Jorge V, Sanjana Pampati, Catherine N Rasberry, Nicole Liddon, Marci Hertz, Greta Kilmer, Melissa Heim Viox, Sarah Lee, Neha K Cramer, Lisa C Barrios, et al. 2021. "Association of Children's Mode of School Instruction with Child and Parent Experiences and Well-being During the COVID-19 Pandemic—COVID Experiences Survey, United States, October 8–November 13, 2020". Centers for Disease Control and Prevention, *Morbidity and Mortality Weekly Report* 70 (11): 369.

von Hippel, Paul T, Joseph Workman, and Douglas B Downey. 2018. "Inequality in Reading and Math Skills Forms Mainly Before Kindergarten: A Replication, and Partial Correction, of 'Are Schools the Great Equalizer?'" Sage Publications, *Sociology of Education* 91 (4): 323–357.

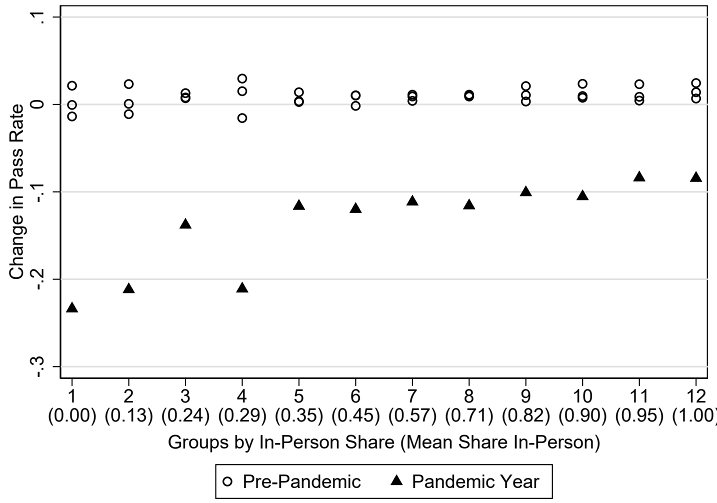
West, Martin R, and Robin Lake. 2021. *How Much Have Students Missed Academically Because of the Pandemic? A Review of the Evidence to Date.* Center on Reinventing Public Education.

Wyse, Adam E, Eric M Stickney, David Butz, Amanda Beckler, and Catherine N Close. 2020. “The Potential Impact of COVID-19 on Student Learning and How Schools Can Respond”. Wiley Online Library, *Educational Measurement: Issues and Practice* 39 (3): 60–64.

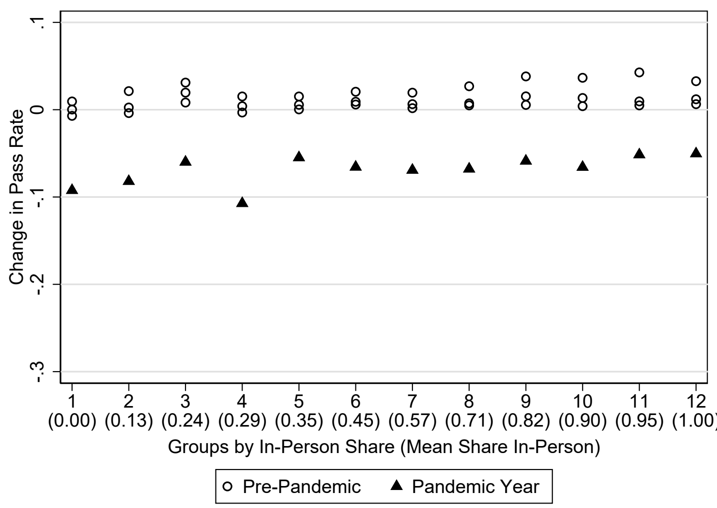
5 Tables and Figures

Figure 1: Changes by Schooling Mode

(a) Math Scores



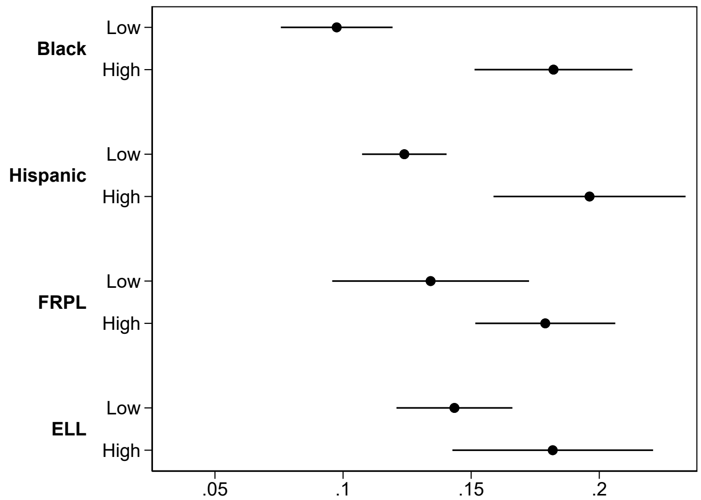
(b) ELA Scores



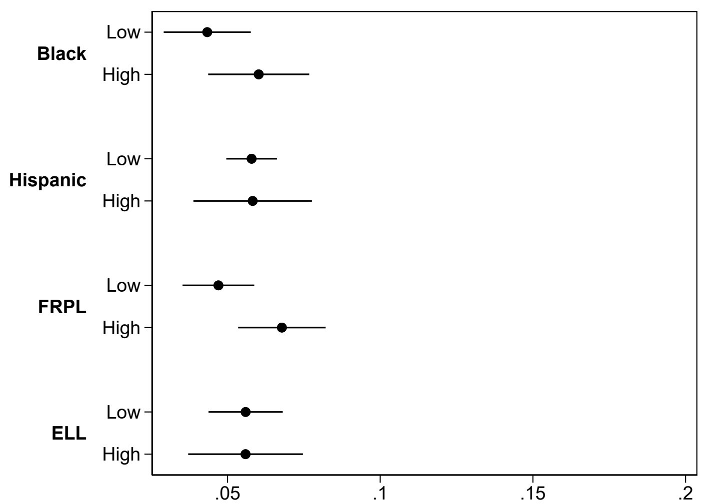
Notes: These figures show the relationship between bins of in-person shares and changes in pass rates, for the pandemic and pre-pandemic years. Bins are labeled with the average in-person share in the bin. All test scores are for Grades 3–8. Details of the testing by state are in Appendix B.

Figure 2: Effects by Demographic Splits

(a) Math Scores



(b) ELA Scores



Notes: These figures show regression coefficients for regressions by district demographics. Groupings are based on splitting the sample of districts in half (weighted by enrollment) based on each demographic group. Regressions are run separately for each group, following the format of Column (2) of Table 2. These regressions include time-varying demographic controls (race/ethnicity, FRPL share, unemployment rate) as well as district and year fixed effects. All regressions are weighted by district enrollment. Standard errors are clustered by district. All test scores are for Grades 3–8. Details of the testing by state are in Appendix B.

Table 1: Summary Statistics

Panel A: Demographic Characteristics and Schooling Mode

	Districts	Avg Years	% In-Person	% Hybrid	% Virtual	% Black & Hispanic	% FRPL	% ELL
CO	151	4.7	43.9	26.8	29.2	38.9	41.8	11.8
CT	160	5.0	58.5	31.3	10.2	37.0	38.1	7.6
MA	284	4.0	27.4	54.4	18.2	28.0	0.0	9.9
MN	340	4.9	16.2	69.1	14.7	18.6	35.2	7.5
MS	134	4.9	66.9	18.8	14.3	51.5	73.8	3.2
OH	606	5.0	50.5	32.3	17.1	19.8	30.1	3.4
RI	50	2.9	48.2	42.4	9.4	33.9	47.0	9.2
VA	132	5.0	9.7	51.8	38.6	38.0	42.3	8.3
WI	396	5.0	58.6	21.1	20.3	20.7	38.7	6.0
WV	55	5.0	37.6	41.4	17.4	6.2	49.3	1.0
WY	48	3.0	88.3	4.9	0.7	14.8	36.4	2.9
Overall	2356	4.7	38.9	39.5	21.4	28.6	35.7	6.9

Panel B: Pass Rates

	Math				ELA			
	2021 Pass	2019 Pass	Diff	Prior Range	2021 Pass	2019 Pass	Diff	Prior Range
CO	27.5	35.2	-7.6	0.1-2.2	43.0	46.2	-3.2	1.2-2.5
CT	37.6	48.4	-10.8	1.3-1.7	48.5	56.0	-7.4	-1.4-1.3
MA	33.7	48.8	-15.1	-0.1-1.0	46.1	52.1	-6.0	1.1-2.2
MN	44.4	57.5	-13.1	-2.0--1.2	51.8	59.7	-7.9	-0.8-0.1
MS	63.1	77.5	-14.4	1.6-4.1	67.8	76.1	-8.3	1.8-4.5
OH	51.5	66.2	-14.7	0.1-2.5	58.1	66.3	-8.2	0.8-6.2
RI	20.5	30.4	-10.0	2.6-2.6	32.9	38.9	-6.0	4.7-4.7
VA	47.2	79.2	-32.0	-2.9-5.2	67.0	76.1	-9.0	-1.7-0.3
WI	34.2	44.1	-9.8	-0.4-1.0	34.0	41.4	-7.4	-2.1-1.8
WV	28.0	38.8	-10.8	1.2-2.7	40.0	46.2	-6.2	-2.4-1.0
WY	49.7	53.9	-4.2	2.4-2.4	54.6	56.7	-2.2	1.7-1.7
Overall	39.8	52.7	-13.0	0.4-2.2	49.4	56.0	-6.5	0.3-2.4

Notes: This table shows summary statistics for the states included in the sample. In Panel A, "Districts" represents the number of school districts included in the sample due to available data. "Avg Years" represents the average number of years of sample data for districts in the state. Data on learning modes are drawn from the COVID-19 School Data Hub. The schooling mode variables ("% In-Person", "%Hybrid", "%Virtual") represent the average % of the school year that the state's school districts offered each schooling mode. Demographic variables include the average proportion of students that are Black and Hispanic, eligible for free and reduced price lunch (FRPL) and English language learners (ELL) for districts in each state. In Panel B, all summary statistics are weighted by district-level enrollment. "Prior Range" indicates the range of year-on-year test score changes pre-pandemic. Details on test score data for each state are provided in Appendix B.

Table 2: Schooling Mode and Test Score Changes

Panel A: Math				
	(1)	**(2)**	**(3)**	**(4)**
	Pass Rate	**Pass Rate**	**Pass Rate**	**Pass Rate**
% In-Person * 2021	0.152	0.158	0.0741	0.0729
	(0.0123)	(0.0111)	(0.00788)	(0.00808)
Observations	11143	11103	11103	11103
District FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Demographics	NO	YES	YES	YES
State X Year	NO	NO	YES	YES
Commute Zone X Year	NO	NO	NO	YES

Panel B: ELA				
	(1)	**(2)**	**(3)**	**(4)**
	Pass Rate	**Pass Rate**	**Pass Rate**	**Pass Rate**
% In-Person * 2021	0.0529	0.0591	0.0332	0.0432
	(0.00532)	(0.00483)	(0.00611)	(0.00601)
Observations	11170	11128	11128	11128
District FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Demographics	NO	YES	YES	YES
State X Year	NO	NO	YES	YES
Commute Zone X Year	NO	NO	NO	YES

Notes: This table shows the relationship between district in-person share and test scores. Non-in-person time includes both hybrid and virtual. All regressions are weighted by district enrollment. Controls are listed at the bottom of the table. Demographic controls include race/ethnicity (shares of White, Black and Hispanic students), share of students eligible for free or reduced price lunch, share of English language learner students and unemployment rate. Columns (3) and (4) contain state- or commuting zone-fixed effects interacted with year dummies. Outcome is pass rate for students in Grades 3–8. Standard errors are clustered by district. Details on test score data for each state are provided in Appendix B.

Table 3: Robustness

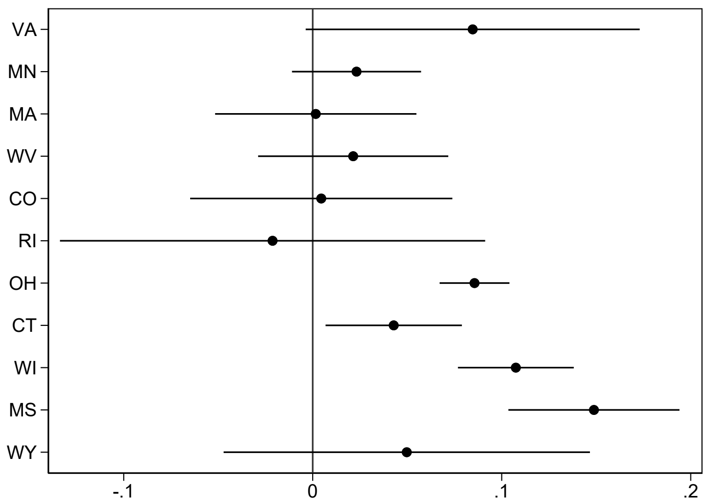
Panel A: By Grade		
	Math	**ELA**
All	0.158 (0.010)	0.061 (0.005)
Grade 3	0.123 (0.010)	0.051 (0.007)
Grade 4	0.143 (0.010)	0.054 (0.007)
Grade 5	0.157 (0.014)	0.081 (0.007)
Grade 6	0.178 (0.020)	0.050 (0.006)
Grade 7	0.166 (0.014)	0.069 (0.007)
Grade 8	0.181 (0.015)	0.054 (0.007)
Panel B: Participation		
	Math	**ELA**
All	0.158 (0.011)	0.059 (0.005)
High Bound	0.067 (0.018)	-0.013 (0.011)
Low Bound	0.210 (0.017)	0.144 (0.014)
Panel C: Alternative Cutoffs		
	Math	**ELA**
All	0.190 (0.014)	0.059 (0.007)
Below Pass	-0.062 (0.018)	-0.019 (0.014)
Advanced Pass	0.092 (0.009)	0.046 (0.005)

Notes: This table shows robustness analyses. All regression follow the form of Column (2) in Table 2. Panel A estimates the impacts by grade. These data are missing for Massachusetts, so the first row estimates the overall impact for the subset of states with data. Panel B generates bounds based on test participation by district; these participation data are available for all states. The "High Bound" assumes that all non-participating students would have passed the test. The "Low Bound" assumes that none of the non-participating students would have passed. Panel C estimates the impact on alternative test score cutoffs (we are missing data from Ohio and Virginia). "Below Pass" is the lowest cutoff in the state and "Advanced Pass" is the highest. Standard errors are clustered by district.

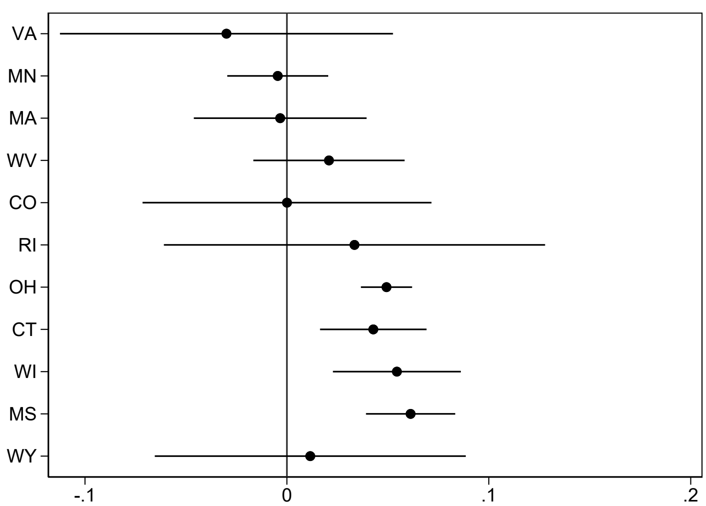
Appendix A: Additional Tables and Figures

Appendix Figure A.1: Effects by State

(a) Math Scores



(b) ELA Scores



Notes: These figures show regression coefficients by state from regression of the form in Column (2) of Table 2. Standard errors are clustered by district.

Appendix Table A.1: Determinants of Schooling Mode

	Correlation (No FE)	**Correlation (State FE)**
Prev Pass Rate	0.520 (0.037)	0.689 (0.030)
Share Black	-0.533 (0.026)	-0.779 (0.024)
Share Hispanic	-0.331 (0.031)	-0.371 (0.032)
Share FRPL	-0.010 (0.021)	-0.204 (0.023)
Share ELL	-1.237 (0.068)	-0.947 (0.061)
Avg Case Rate	0.890 (0.061)	0.381 (0.058)
Repub Vote Share	0.010 (0.000)	0.010 (0.000)

Notes: This table shows regressions of the share of days in-person during the 2020-21 school year on district characteristics. The share in-person measures the share of time during the 2020-21 school year in which the district offered full time in-person instruction. All cells represent separate regressions, so these are binary relationships. Standard errors are in parentheses. Regressions are weighted by district enrollment.

Appendix Table A.2: Separating Hybrid and Virtual Learning

	(1)	(2)
	Math	ELA
Pass		
% In-Person * 2021	0.223	0.101
	(0.0225)	(0.0112)
% Hybrid * 2021	0.0935	0.0614
	(0.0253)	(0.0124)
Observations	11103	11128
District FE	YES	YES
Year FE	YES	YES
Demographics	YES	YES

Notes: This table shows the relationship between district in-person share, district hybrid share and test score changes. Hybrid schooling mode is defined as any mode which provides some in-person learning but does not provide 5 full days of in-person learning. The omitted category is virtual learning. Regressions take the form of Column (2) of Table 2. Standard errors are clustered by district.