The Decline in Standard Exam Pass Rates Due to Schooling Modes During the 2020–2021 Academic Year in the United States*

Julian Marrero

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Abstract

This report assesses the influence of the type of instruction—specifically, in-person compared to a mix of online and traditional learning or entirely online—provided by US school districts during the 2020–2021 academic year on the pass rates of standard exams for students from the third to the eighth grade across eleven states. We observed a decrease in pass rates from 2019 to 2021, with an average drop of 12.8 percentage points for mathematics and 6.8 for English language arts (ELA). By examining the differences in educational modes within the same state and commuting zones, our findings suggest that districts that maintained full in-person instruction experienced notably smaller reductions. Furthermore, the benefits of in-person education were more pronounced in districts with a higher percentage of African American students.

Contents

*A GitHub Repository containing all data, R code, and any additional files used in this report is located at: https://github.com/julianmarrero/Pandemic-Schooling-Mode-and-Student-Test-Scores; Replication on Social Science Reproduction platform located at: https://doi.org/10.48152/ssrp-8t9e-vq85

1 Introduction

During the 2020–2021 academic year, U.S. schools faced unprecedented challenges due to the COVID-19 pandemic, leading to various instructional approaches including virtual, in-person, and hybrid models. This period of educational disruption prompted an investigation into its effects on standardized test pass rates for students in grades 3-8 across 11 states (McLeod and Dulsky, 2021; Kaufman and Diliberti, 2021). The study revealed a significant decline in pass rates from 2019 to 2021, averaging a drop of 12.8 percentage points in math and 6.8 in ELA, with the largest decreases observed in Virginia and the smallest in Wyoming. It was found that less in-person instruction and higher populations of Black students were associated with larger declines.

To assess the causal impact of these varied instructional modes on pass rates, the report utilized a panel data approach, controlling for local economic and demographic factors. The analysis indicated that districts with full in-person or hybrid learning modes experienced significantly smaller declines in pass rates compared to those with fully virtual learning. Notably, in-person learning showed a positive interaction with districts having a higher proportion of Black students and those eligible for free and reduced-price lunch, particularly in math scores.

This research contributes to the understanding of how educational disruptions during the COVID-19 pandemic have affected student achievement across the United States. It underscores the potential long-term educational implications of the pandemic and suggests targeted interventions may be necessary to address learning losses, especially among the most vulnerable student populations (Kogan and Lavertu, 2021; Fuchs-Schündeln et al., 2021). The findings also caution against the future use of school closures as a response to crises, highlighting the need for policies that support continued access to in-person learning.

This paper will follow a reproduction of Jack, Rebecca, Clare Halloran, James Okun, and Emily Oste findings from Pandemic Schooling Mode and Student Test Scores: Evidence from US School Districts. This paper seeks to replicate the following research claims: (1) Students learn better with in-person schooling compared to online/hybrid models and (2) The benefits of in-person schooling are more pronounced in districts with a higher percentage of Black students. This reproduction was conducted using the statistical programming language R (R Core Team, 2020). The following packages were used in the analysis: dplyr (Wickham et al., 2022), tidyr (Wickham et al., 2024), haven (Wickham et al, 2023), knitr (Xie, 2014), gt (Iannone, 2024), ggplot2 (Wickham, 2016), forcats (Wickham, 2023), plm (Croissant, 2008), lmtest (Zeileis and Hothorn, 2002), sandwich (Zeileis, 2006), stargazer (Hlavac, 2022), rmarkdown (Xie et al, 2018).

The paper begins with a discussion of the data source used, the methodologies employed, and a review of the variables used for the reproduction. Then, a reproduction of various tables and figures will be conducted to verify the claims made in the original paper. The paper then concludes with a discussion of the findings, limitations, and future research to be done.

2 Data

2.1 Source

The paper used for this replication is from the American Economic Review: Insights which discusses the effect of different schooling methods (i.e., in-person, online, and hybrid) on US student pass rates for mathematics and English (Jack et al., 2023). My reproduction aims to address the findings made from the original paper and discuss the implications of these findings. The claims that will be discussed are: (1) Does the mode of schooling affect a student's ability to learn? (2) Does a student's background affect what mode of schooling works best for them?

2.2 Methodology

This paper will replicate the summary statistics by States, the pairwise correlations between in-person learning on district demographic and pandemic variables, and finally the average change in pass rates of state standardized tests in Spring 2021 versus Spring 2016-2019. These figures and tables will be replicated using the cleaned dataset supplied by the original paper.

The raw data extracted in the original paper came from seven sources: "(1) state test score data from the 11 states, (2) schooling mode (learning model) data from the COVID-19 School Data Hub, (3) average COVID-19 case counts from USA Facts (4) National Center for Education Statistics Common Core of Data Demographic Data, (5) commuting zone labor market data, (6) Bureau of Labor Statistics unemployment data, and (7) Republican vote share in the 2020 election" (Jack et al. 2023).

2.3 Features

Within the cleaned dataset provided in the original paper (2023) by Jack et al, there are key variables to note that were utilized in the reproductions. For each state in the sample, the average percentage of schooling modes provided in the school districts was noted (including in-person, hybrid, and virtual). This allows us to identify which type of schooling mode is the most effective for learning by comparing the pass rates of students in different states and comparing the variation of schooling modes.

Within the schooling districts in each state, the share of Black and Hispanic students was noted. This was utilized in the original paper to identify if minorities within these districts had any preferences in schooling mode. Additionally, the percentage of students in each state participating in various programs such as the Free/Reduced Price Lunch program (FRPL) and English Language Learners (ELL) was noted to indicate if students from lower-socioeconomic classes also had different preferences in schooling mode.

The last variable to note is the pass rates for math and ELA from students in grades 3-8 in each school district from the years 2016-2019. This was measured by students who scored proficient or above in ELA and math state assessments.

3 Results

Figure 1 displays some summary statistics of the dataset depicting key aspects of each state. "Number of Districts" refers to the number of schooling districts included in the sample. "Average Years" is the average number of years of assessment data for that given state. "In-Person(%)", "Hybrid(%)", and "Virtual(%)" refer to the average percent of the school year that the state school's district offered for each schooling mode. "Black & Hispanic(%)" refers to the percent of students in the schooling districts of that state that identify as Black or Hispanic. "Free/Reduced Lunch(%)" and "English Language Learners(%)" refer to the percentage of students that qualify for these programs. Massachusetts does not report Free/Reduce Lunch program data thus it is omitted from the table.

Summary of Statistics								
State	Number of Districts	Average Years	In-Person (%)	Hybrid (%)	Virtual (%)	Black & Hispanic (%)	Free/Reduced Lunch (%)	English Language Learners (%)
CO	136	4.713235	28.9	43.8	27.3	37.8	41.4	11.5
CT	160	4.950000	47.4	36.3	9.1	35.1	37.4	6.7
MA	284	4.000000	27.4	54.4	18.2	26.9	NaN	9.1
MN	340	4.891176	16.2	69.1	14.7	17.6	36.4	7.5
MS	134	4.895522	66.7	18.4	14.9	51.5	73.9	2.3
OH	606	5.000000	50.0	32.1	17.1	19.0	43.7	3.1
RI	37	2.918919	44.5	41.8	8.2	31.5	44.7	8.8
VA	132	5.000000	9.7	51.8	38.6	37.4	40.4	8.7
WI	396	4.989899	51.5	22.1	18.4	19.9	39.1	5.4
WV	55	5.000000	37.6	41.4	17.4	6.1	49.2	1.1
WY	48	3.000000	86.5	6.2	0.7	14.7	37.0	3.0

Figure 1: Summary Statistics by State

From Figure 1, in-person learning rates are highest in Wyoming (86.5%) and Mississippi (66.7%) and lowest in Minnesota (16.2 percent) and Virginia (9.7 percent). Contrarily, Virginia, and Colorado have the highest share of district time spent in fully virtual learning at 38.6% and 27.3%, respectively. States in the sample vary across demographic characteristics as well, including their share of students who are Black and Hispanic, eligible for FRPL programs, and those who are ELLs.

Figure 2 displays the linear regression analyses that assess the association between various demographic and educational variables with the share of in-person learning. Robust standard errors are reported in the parentheses for each separate regression.

From Figure 2 the "Previous Pass Rate" row indicates a positive association with in-person learning across all models, with the strongest association observed in the state fixed effects model. The "Share Black" and "Share Hispanic" rows have negative coefficients in all three models suggesting that districts with higher proportions of Black or Hispanic students tend to have a lower share of in-person learning. The magnitude of the coefficients increases (more negative) when state fixed effects are included, which could indicate that within states, districts with higher proportions of these demographic groups had even less in-person learning. The negative coefficients in Share FRPL indicate that districts with a higher proportion of students eligible for free or reduced-price lunch (a common indicator of lower socioeconomic status) are associated with a lower share of in-person learning. This negative association is consistent across all model specifications. There is a substantial negative association between the proportion of ELL students in a district and the share of in-person learning. The coefficients are quite large compared to other variables, suggesting a strong relationship. The fact that the standard errors are relatively small compared to the coefficients suggests that the coefficients are statistically significant.

	No Fixed Effects	State Fixed Effects	Commute Zone Fixed Effects
Previous Pass Rate	0.140 (0.052)	0.585 (0.042)	0.541 (0.035)
Share Black	-0.463 (0.028)	-0.745 (0.028)	-0.736 (0.025)
Share Hispanic	-0.466 (0.046)	-0.341 (0.045)	-0.298 (0.043)
Share FPRL	-0.111 (0.036)	-0.250 (0.034)	-0.333 (0.029)
Share ELL	-1.349 (0.080)	-0.880 (0.070)	-0.776 (0.066)

Figure 2: Regression Analysis of In-Person Learning Share by District Demographics and Pandemic Impact

In Figure 3 it displays the average pass rate for each state for both the math and ELA state assessments. The grey points are the average pass rates from 2016-2019. The black points are the pass rates from the 2020-2021 academic session. As seen in Figure 3, for the ELA state exams, only Wisconsin and Rhode Island had a higher pass rate in 2021 compared to 2016-2019, whereas all of the other states had a decliine, with Colorado with the largest decline.

For the math state exams, only Ohio, Wyoming, and Rhode Island had higher pass rates in 2021 compared to 2016-2019. All of the other states had a lower pass rate, with Connecticut having the highest drop in pass rates.

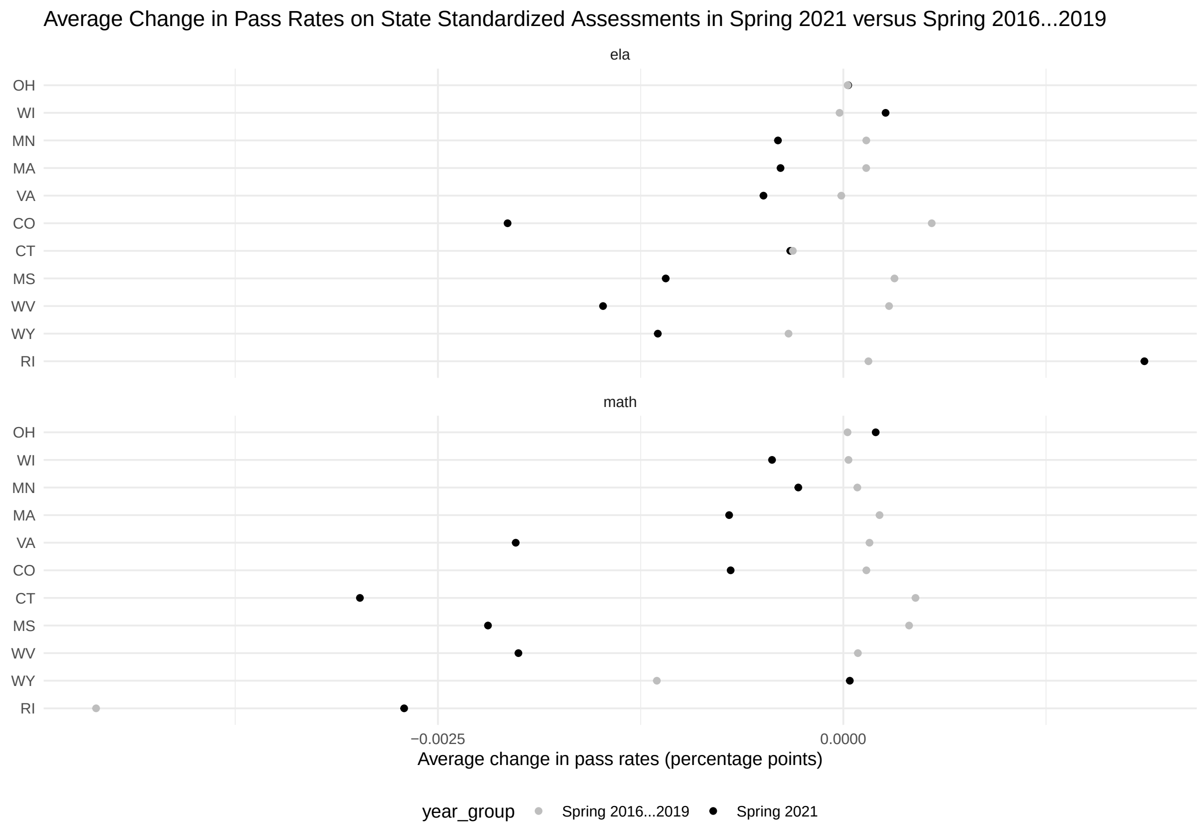

Figure 3: Average Change in Pass Rates on State Standardized Assessments in Spring 2021 versus Spring 2016–2019

4 Discussion

4.1 Findings

From Figure 2, the inclusion of state and commute zone fixed effects generally increases the magnitude of the coefficients for the Previous Pass Rate and decreases the magnitude for demographic variables, which may reflect underlying structural differences that are accounted for by the fixed effects. The coefficients in the fixed effects models (state and commute zone) are likely to be more reliable as they control for unobserved heterogeneity at these levels. This could mean that regional factors play a significant role in the relationship between district demographics and the mode of schooling.

From Figure 3, we can see that the majority of states had a decline in passing rates for both math and ELA state exams in the 2020-2021 academic period compared to 2016-2019, with Wisconsin, Ohio, Rhode Island, and Wyoming being outliers from the rest. This suggests, that the use of virtual and hybrid learning is less effective than in-person learning as the declines in pass rates were quite significant for many of the states.

Cross-referencing the data from Figure 1 and Figure 3 we can see that the states with the highest percentage of in-person learning tended to be the states that had an increase in pass rates compared to the other states. Additionally, these states typically had lower rates of students in the FRPL and ELL programs. This may suggest that students from lower socioeconomic backgrounds perform worse than students from better socioeconomic backgrounds. The cause of this observation may be due to a range of variables (many of which are not in the scope of the data collected). One suggestion may be that due to their economic situation, they may face other issues that can hold them back from performing as well as their other peers. This may be an indication that the government should provide programs to assist these students with their studies or to provide programs for lower socioeconomic families to aid in their economic struggles. This would alleviate pressure from the children in these families allowing them to have more focus on their studies.

4.2 Accounting for Bias

The authors of the original paper were concerned that the variation in enrollment or participation in the test may bias their results. Due to the COVID-19 pandemic, some students left the US public school system and thus would not appear in the testing pool. Jack, Rebecca, Clare Halloran, James Okun, and Emily Oste, noticed that there were larger declines in enrollment in areas with more virtual learning, potentially causing these school districts to have systematically lower or higher scores. As Jack et al. observed the enrollment directly, they incorporated this variable into their regression model to account for this potential bias (Jack et al., 2023).

4.3 Limitations

One limitation of this paper is that the data used for analysis was the cleaned dataset provided by the (2023) original report made by Jack et al. Therefore, there may be other variables that may have been of interest that were excluded from the analyses that may have affected the findings. The choice of using the pre-cleaned dataset was made to save time and effort in making this report.

Additionally, throughout this report, the analysis conducted was done on the aggregate scores/data from the students in grades 3-8. It would have been useful to conduct further analysis of the separate grades individually, as there may be variation of pass rates between grades due to the attention span of students at different ages.

Furthermore, the data utilized only represents 11 out of the 50 states in the U.S. Therefore, the findings may not be representative of the entire country, as different states employed different regulations for schooling mode during the COVID-19 pandemic.

4.4 Future Research

Some potential future research that can be conducted is analyzing the impact of the different schooling modes for higher grade levels such as high school students. As high school students study a greater range of subjects rather than just math and English, analyzing their grades using the different schooling modes may indicate if the trend is consistent among all areas of study.

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