COVID-19 and Education Outcomes: How Demographics and School Closures Affected Learning

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Abstract

In this paper, I explore how racial and socioeconomic test score gaps have changed since the onset of the COVID-19 pandemic and to what extent teaching modality was responsible for the growth in score gaps. Additionally, I analyze how test score gaps evolved from 2022 to 2023. This paper addresses the differences between individual-level score gaps and district-level gaps. Given that past literature finds growth in test score gaps due to the COVID-19 pandemic, I attempt to identify whether high-minority and high-poverty school districts are falling behind as a whole or if the widening in test score gaps is due to minority and economically disadvantaged students falling behind peers in their district. I use a triple-difference (DDD) model to determine whether in-person learning affected the growth of test score gaps and to identify interactions between district- and individual-level effects. I find that (1) From 2019 to 2022, the test score gap between high-poverty and low-poverty school districts widened significantly, as did the gap between high-minority and low-minority districts; (2) Districts that spent more of the 2020–2021 school year in person saw smaller drops in test scores, particularly in math; (3) In-person learning reduced score gaps between high- and low-poverty school districts in math but may have widened Black-white score gaps in reading; (4) Within districts, economically disadvantaged students have seen slower recovery from 2022 to 2023 than their classmates; and (5) All significant COVID-related score gaps that appeared between 2019 and 2022 persisted in 2023.

1 Introduction

Students have been falling behind since the start of the pandemic. A January 2023 meta-analysis of studies from 15 countries estimated that the average student experienced learning loss equivalent to 35% of a school year, and that learning deficits have been relatively stable since the early stages of the pandemic.[1] Kuhfeld, Soland, and Lewis[2] find that learning loss in math continued throughout the first two years of the pandemic, whereas learning loss in reading occurred mostly between fall 2020 and fall 2021.

Learning loss continued into the 2022–2023 school year. A report by the NWEA Center for School and Student Progress finds that achievement gains for the 2022–2023 school year were smaller than in pre-pandemic years in all but the youngest grade tested (3rd grade) across all race/ethnicity groups. At the end of the school year, the average student was 4.1 months behind in reading and 4.5 months behind in math. Growth in reading achievement for grades 6-8 has been especially slow, lagging behind pre-COVID gains by nearly 20%.[3]

My analysis shows that differences between districts drove the widening of test score gaps from 2019 to 2022 and that differences within districts are a major driver of gaps in 2023. My findings add to the literature by (1) presenting a triple differences model for test score gaps through 2023; (2) studying interactions between modality and district demographics; (3) including COVID-19 death rates in a model of test score gaps; and (4) examining the interaction of socioeconomic and racial subgroups with overall district composition to gain insight into the mechanisms driving test score gaps.

I use data on test scores, school modality, and demographic information reported at the local educational agency (LEA) level. Each school district is an LEA, but other educational agencies such as charter schools also comprise their own LEA.[4] Data on COVID cases are available at the county level and are linked to score, modality, and demographic data, as described in Section 2.2. Using these data, I estimate the effect of the pandemic on test scores. I use a difference-in-differences model

1. Bastian A. Betthäuser, Anders M. Bach-Mortensen, and Per Engzell, "A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic | Nature Human Behaviour," *Nature Human Behavior* 7 (January 30, 2023): 375–385, accessed February 2, 2024, https://www.nature.com/articles/s41562-022-01506-4.

2. Megan Kuhfeld, James Soland, and Karyn Lewis, "Test Score Patterns Across Three COVID-19-Impacted School Years," *Educational Researcher* 51, no. 7 (October 2022): 500–506, ISSN: 0013-189X, 1935-102X, accessed February 2, 2024, https://doi.org/10.3102/0013189X221109178, http://journals.sagepub.com/doi/10.3102/0013189X221109178.

3. Karyn Lewis and Megan Kuhfeld, *Education's long COVID: 2022–23 achievement data reveal stalled progress toward pandemic recovery* (Northwest Evaluation Association, July 2023).

4. Throughout this paper I will refer to local education agencies as "districts", particularly in discussions of "district-level effects".

to determine how the test scores of different subgroups changed from 2019 to 2023. I estimate the effect of modality on test scores by comparing the change in scores for districts with a high percentage of the 2020–2021 school year spent in-person to districts with less in-person instruction. I interact modality with race and socioeconomic status to estimate the effect of modality on particular group differences. A causal interpretation of these comparisons is valid under the assumption of parallel trends–that score differences between districts and groups would have been stable if not for the COVID-19 pandemic. As there is non-negligible deviation from parallel trends for some of these tests, I utilize additional techniques described in section 3.1.

Before the COVID-19 pandemic, research on learning loss focused on summer breaks. Atteberry and McEachin[5] estimated that students lose between 17% and 28% of the previous school year's learning in reading/language arts (RLA) and between 25% and 34% in math during summer break.

There is also evidence to suggest that summer learning loss leads to a growing score gap. Hayes and Grether[6] examined test scores of students in New York City and concluded that upward of 80% of the difference in progress between students in the wealthiest and whitest schools and students in the poorest, less white schools was associated with summer months when children were not in school. A more recent study of test score data from Baltimore showed that the socioeconomic test score gap did not grow throughout the school year but grew significantly over the summer, suggesting that the growth in score gaps from 1st to 9th grade is attributable to unequal summer learning loss.[7] Other studies, however, have estimated that approximately 4% of summer learning loss is explained by race and socioeconomic status (SES), suggesting that there are other more important factors.[8] Regardless, this research suggests that test score gaps grow when students are not attending school.

In line with this finding, experts expected test score gaps to increase during the COVID-19 pandemic, when children were not attending school in person. In a survey conducted in November 2020, education researchers predicted that socioeconomic gaps would grow by 0.3 standard deviations for math and 0.25 standard deviations for reading by 2021. This is approximately equivalent to a rela-

5. Allison Atteberry and Andrew McEachin, "School's Out: The Role of Summers in Understanding Achievement Disparities," Publisher: SAGE PublicationsSage CA: Los Angeles, CA, *American Educational Research Journal*, July 8, 2020, accessed February 2, 2024, https://doi.org/10.3102/0002831220937285, https://journals.sagepub.com/stoken/default+domain/GBRTK2UCCZCUMP8IB6RN/full.

6. Donald P. Hayes and Judith Grether, *The School Year and Vacations: When Do Students Learn?*, ERIC Number: ED037322 (April 19, 1969), accessed February 2, 2024, https://eric.ed.gov/?id=ED037322.

7. Karl L. Alexander, Doris R. Entwisle, and Linda Steffel Olson, "Lasting Consequences of the Summer Learning Gap," *American Sociological Review* 72, no. 2 (April 2007): 167–180, ISSN: 0003-1224, 1939-8271, accessed March 20, 2024, https://doi.org/10.1177/000312240707200202, http://journals.sagepub.com/doi/10.1177/000312240707200202.

8. Atteberry and McEachin, "School's Out."

tive achievement loss of 5 months in math and 6 months in reading.[9] Analysis in June 2020 estimated that the average student could fall behind by seven months during the pandemic. Projected learning losses were 10.3 months for Black students, 9.2 months for Hispanic students, and over a year for low-income students. They estimated that white students could see a 1.6 percent reduction in lifetime earnings due to this learning loss; for Black and Hispanic students, the reduction in earnings could be more 3 percent. Furthermore, they estimate a drop in GDP of $173 billion to $271 billion per year as a result.[10]

One of the most important education policy issues in 2020 and 2021 was determining when schools should return to fully in-person learning. During the height of the pandemic, experts suggested that in-person school would be better for learning than remote or hybrid education. Organizations such as the American Academy of Pediatrics recommended a safe return to in-person learning as early as the summer of 2020.[11] The US Department of Education claimed that in-person education improves academic outcomes and recommended returning to in-person schooling as public health would allow. To facilitate this, the American Rescue Plan Act of 2021 provided almost $122 billion to schools through Elementary and Secondary School Emergency Relief (ESSER) funds, which could be used to improve the safety of in-person instruction.[12]

Ex post studies suggest that the effects of pandemic learning loss have been unequal. Schools with higher poverty rates are further behind their counterparts[13];[14] this gap is more pronounced in math scores than in reading scores.[15] Learning loss in both reading and math was worse in high-poverty school districts, with the disparity mainly increasing in the 2020–2021 academic year.[16]

9. Drew H. Bailey et al., "Achievement Gaps in the Wake of COVID-19," Publisher: American Educational Research Association, *Educational Researcher* 50, no. 5 (June 1, 2021): 266–275, ISSN: 0013-189X, accessed February 2, 2024, https://doi.org/10.3102/0013189X211011237, https://doi.org/10.3102/0013189X211011237.

10. Emma Dorn et al., "COVID-19 and learning loss—disparities grow and students need help," McKinsey & Company, December 8, 2020, accessed March 20, 2024, https://www.mckinsey.com/industries/public-sector/our-insights/covid-19-and-learning-loss-disparities-grow-and-students-need-help.

11. "COVID-19 Guidance for Safe Schools and Promotion of In-Person Learning," American Academy of Pediatrics, September 8, 2022, accessed February 2, 2024, https://www.aap.org/en/pages/2019-novel-coronavirus-covid-19-infections/clinical-guidance/covid-19-planning-considerations-return-to-in-person-education-in-schools/.

12. "Supporting Students During the COVID-19 Pandemic: Maximizing In-Person Learning and Implementing Effective Practices for Students in Quarantine and Isolation," U.S. Department of Education, accessed February 2, 2024, https://www.ed.gov/coronavirus/supporting-students-during-covid-19-pandemic.

13. Erin M Fahle et al., *School District and Community Factors Associated With Learning Loss During the COVID-19 Pandemic*, May 2023, accessed March 17, 2024, https://educationrecoveryscorecard.org/wp-content/uploads/2023/05/ExplainingCOVIDLosses.pdf.

14. Betthäuser, Bach-Mortensen, and Engzell, "A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic | Nature Human Behaviour."

15. Dan Goldhaber et al., *A Comprehensive Picture of Achievement Across the COVID-19 Pandemic Years: Examining Variation in Test Levels and Growth Across Districts, Schools, Grades, and Students*, May 2022, accessed March 17, 2024, https://caldercenter.org/sites/default/files/CALDER%20Working%20Paper%20266-0522_0.pdf.

16. Kuhfeld, Soland, and Lewis, "Test Score Patterns Across Three COVID-19-Impacted School Years."

Furthermore, there is evidence that younger students who were already performing worse on tests before the pandemic have experienced greater learning loss than high-achieving students.[17] There is already a trend of increasing inequality in education. Owens, Reardon, and Jencks[18] noted an increasing socioeconomic score gap in the US, finding that "between-district income segregation of families with children enrolled in public school increased by over 15% from 1990 to 2010."

It is also well-established that in-person instruction led to better educational outcomes,[19],[20] particularly for younger students.[21,22] Although the test score data I use are not separated by grade, it is important to consider that policies affect children differently depending on their age– a consideration that is unfortunately obscured in my analysis. Despite the initial differences by teaching modality, it does not appear that school districts that spent more time in person experienced better recovery after the initial drop in test scores. Halloran et al.[23] examine "recovery rates," defined as "the share of the 2019–2021 test score decline that is recovered by Spring 2022." They find that recovery rates varied widely by state and district, but not by the rate of in-person schooling in the 2020–2021 school year. This suggests that the effect of teaching modality may have been limited to the 2020–2021 school year, when learning formats varied. See Figures C1, C2, C3, C4. This analysis explores the change in scores between 2019 and 2022, which captures both the initial drop and the initial recovery but does not enable me to disentangle the unique effects of each period. In addition, I examine the recovery from 2022 to 2023. I find evidence for the modality-related test score gap that Halloran et al. attribute to the 2020–2021 school year and show that it had not closed by spring 2023.

Regarding the effects of teaching modality on score gaps, E. M. Fahle et al.[24] found no significant

17. Véronique Irwin et al., "Report on the Condition of Education 2023," May 2023,

18. Ann Owens, Sean F. Reardon, and Christopher Jencks, "Income Segregation Between Schools and School Districts," Publisher: American Educational Research Association, *American Educational Research Journal* 53, no. 4 (August 1, 2016): 1159–1197, ISSN: 0002-8312, accessed March 20, 2024, https://doi.org/10.3102/0002831216652722, https://doi.org/10.3102/0002831216652722.

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

20. E. M. Fahle et al., *School District and Community Factors Associated With Learning Loss During the COVID-19 Pandemic.*

21. Rebecca Jack et al., "Pandemic Schooling Mode and Student Test Scores: Evidence from US School Districts," *American Economic Review: Insights* 5, no. 2 (June 1, 2023): 173–190, ISSN: 2640-205X, 2640-2068, accessed March 18, 2024, https://doi.org/10.1257/aeri.20210748, https://pubs.aeaweb.org/doi/10.1257/aeri.20210748.

22. Svenja Hammerstein et al., "Effects of COVID-19-Related School Closures on Student Achievement-A Systematic Review," Publisher: Frontiers, *Frontiers in Psychology* 12 (September 16, 2021), ISSN: 1664-1078, accessed March 20, 2024, https://doi.org/10.3389/fpsyg.2021.746289, https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2021.746289/full.

23. Clare Halloran et al., *Post COVID-19 Test Score Recovery: Initial Evidence from State Testing Data*, w31113 (Cambridge, MA: National Bureau of Economic Research, April 2023), w31113, accessed February 2, 2024, https://doi.org/10.3386/w31113, http://www.nber.org/papers/w31113.pdf.

24. E. M. Fahle et al., *School District and Community Factors Associated With Learning Loss During the COVID-19*

differences between the effect of in-person learning for different racial and socioeconomic subgroups and could not identify the mechanism by which high-poverty districts performed worse after the pandemic. However, the aforementioned study and Goldhaber et al.[25] concluded that remote and hybrid instruction were significantly more harmful in mid- and high-poverty schools and school districts. Thus, it seems that modality had an effect at the district-level and/or the school-level but, within each school, there is no evidence that students from different backgrounds were impacted significantly differently. Despite this, test score gaps within districts have widened from 2022 to 2023. E. Fahle et al.[26] report that high-income students are recovering roughly twice as fast as low-income students. My findings support these conclusions.

2 Data

2.1 Data Sources

Test score data were retrieved from the Stanford Education Data Archive (SEDA). These data sets are constructed using the United States Department of Education EDFacts data system. I used administrative district-level data from SEDA2023. The data set is extensive, as states are required by federal law to administer standardized tests in math and reading/language arts (RLA) to every student in grades 3 to 8 and report aggregated test score data to EDFacts. Data have been suppressed for several reasons including low participation rate, incomplete data by subgroup, alternate assessments, scores only falling in the top or bottom proficiency category, or cells failing to meet minimum statistical estimation requirements. Data are also suppressed if an estimate is based on too few observations or is too imprecise. In particular, many subgroup estimates are removed at the district level. Because I use these subgroup estimates, my data set is not nationally representative.

I use score estimates from the Year Standardized (YS) scale. These estimates represent standardized averages across all students in grades 3-8. Per the SEDA 2023 documentation: "we standardize the estimates to the 2019 national average in each grade and subject. In this scale, each unit is

Pandemic.

25. Dan Goldhaber et al., "The Consequences of Remote and Hybrid Instruction During the Pandemic," *National Center for Analysis of Longitudinal Data in Education Research*, May 2022, https://www.nber.org/system/files/working_papers/w30010/w30010.pdf.

26. Erin Fahle et al., "The First Year of Pandemic Recovery: A District-Level Analysis," January 2024, https://educationrecoveryscorecard.org/wp-content/uploads/2024/01/ERS-Report-Final-1.31.pdf.

equivalent to a 2019 national standard deviation in the same subject and grade." I use the Empirical Bayes (EB) estimates reported by SEDA. Although these estimates account for differences in testing practices between states, it is still important to note that tests vary in both content and timing.

SEDA also provides socioeconomic, demographic, and segregation data from the American Community Survey, the Common Core of Data (CCD), and the Civil Rights Data Collection (CRDC). An in-depth description of the data collection and cleaning can be found in the documentation for SEDA 5.1[27] and SEDA 2023.[28]

Data on COVID-19 deaths are from the Johns Hopkins Coronavirus Resource Center.[29] Total deaths from COVID-19 are estimated for each county and identified by FIPS code. Estimates were reported daily from January 22, 2020 to March 3, 2023. Data were gathered from many sources such as the World Health Organization, the European Centre for Disease Prevention and Control, and data published by individual states and counties. Population estimates are also reported for each county.

I retrieved data on school modality from HealthData.gov, a website of the United States Department of Health and Human Services. I use their definitions for different modalities:

> In-Person: All schools within the district offer face-to-face instruction 5 days per week to all students at all available grade levels.
>
> Remote: Schools within the district do not offer face-to-face instruction; all learning is conducted online/remotely to all students at all available grade levels.
>
> Hybrid: Schools within the district offer a combination of in-person and remote learning; face-to-face instruction is offered less than 5 days per week, or only to a subset of students.[30]

Data are reported weekly, with each school district classified as in-person, remote, or hybrid. Figure C1 shows the percentage of school districts classified in each modality throughout the 2020–2021

27. S. F. Reardon et al., *Stanford Education Data Archive*, v. 5.0, 2024, https://purl.stanford.edu/cs829jn7849..
28. S. F. Reardon et al., *Stanford Education Data Archive*, v. SEDA 2023, 2024, https://purl.stanford.edu/xt779fj2637.
29. Ensheng Dong et al., "The Johns Hopkins University Center for Systems Science and Engineering COVID-19 Dashboard: data collection process, challenges faced, and lessons learned," Publisher: Elsevier, *The Lancet Infectious Diseases* 22, no. 12 (December 1, 2022): e370–e376, ISSN: 1473-3099, 1474-4457, accessed March 17, 2024, https://doi.org/10.1016/S1473-3099(22)00434-0, https://www.thelancet.com/journals/laninf/article/PIIS1473-3099(22)00434-0/fulltext.
30. CDC School Data Team, *School Learning Modalities, 2020-2021*, accessed March 17, 2024, https://healthdata.gov/National/School-Learning-Modalities-2020-2021/a8v3-a3m3/about_data.

school year. Figures C2, C3, C4 show the average share of the school year that each state spent in each modality.

2.2 Data Cleaning

I use different data sets to examine the Black-white test score gap, the socioeconomic status (SES) test score gap, and general trends for all students. Due to data cleaning and suppression by SEDA, many relevant estimates are missing; to maximize the number of observations included in my sample, I use different restrictions as appropriate. Six different data sets are used in my analysis, which are referred to as Data Sets A - F. Each of these data sets is a subset of all available data. A description of each group is reported in Appendix A and sample composition is shown in Tables A1-6. For each sample, I filter out any school district missing score estimates for the relevant subgroup(s) in 2016, 2017, 2018, 2019, or 2022 so that there is a balanced panel of school districts across years. I repeat this analysis including 2023 scores. Fewer school districts have data reported in 2023, so this analysis is based on a smaller sample, as seen in the sample composition tables in the appendix.

Districts that saw large changes in demographics or enrollment between 2019 and 2022 are flagged in the SEDA 2023 data set. I chose to keep these districts in the sample, which could be a source of bias in my results.

To estimate COVID severity, I calculated the average death rate between September 1, 2020 and June 30, 2021 to capture the whole school year. The rate is:

$$\frac{(deaths_{6.30.21} - deaths_{9.1.20}) \times 1000}{10 \times Population}$$

where $deaths_d$ is the sum of deaths in an area from the onset of the pandemic to date d. It is therefore an average monthly death rate per 1000 people. I use the z-score of this estimate for easier interpretation.

COVID-19 deaths were reported at the county level, but many school districts are not contained within one county. I used data from the National Center for Education Statistics (NCES) to select one county for each local educational agency.[31] For every school district within multiple counties, I selected the county containing the plurality of the school district's land area.

31. Douglas O Geverdt, *Education Demographic and Geographic Estimates Program (EDGE): School District Geographic Relationship Files User's Manual*, NCES 2018-076, accessed February 10, 2024, https://nces.ed.gov/programs/edge/geographic/relationshipfiles.

I used weekly modality data from HealthData.gov to the percentage of the 20202021 school year that each school district spent fully in-person. Data are reported from September 6, 2020 to May 30, 2021. The minimum number of school days required by any US state is 160.[32] Accordingly, I removed data for school districts that reported modality data for fewer than 32 weeks. This ensures that the averages reflect the majority of the school year and avoids bias from temporal differences in modality. I calculated the percentage of the school year that districts were reported as in-person, hybrid, or remote, respectively.

3 Methods

3.1 All Students

I use difference-in-differences analysis to explore changes in trends from 2019 to 2022 and 2023. Using 2019 as a base year, I explore how districts diverged from their 2019 scores and how they recovered from 2022 to 2023. I include district-level fixed effects in all regressions to account for the for the preexisting differences in scores between districts and state-year dummy variables to account for states' different policy responses to the pandemic, beyond school closures. I also weight my estimates by the number of students in each district taking each test (math or reading).

Traditional difference-in-differences analysis relies on the assumption of parallel trends; a "treated" and "untreated" group must have had the same trends prior to an intervention. This does not hold for all groups that I analyze. I use methods introduced by Rambachan and Roth[33] to check for robustness to these differential trends. Essentially, I test the significance of my estimates assuming that the differential trends continued into the post-treatment period and were amplified by up to $\bar{M}$ times the maximum pre-treatment deviation from parallel trends. As stated by Rambachan and Roth:

$$\Delta^{RM} = \{\delta : \forall t \geq 0, |\delta_{t+1} - \delta_t| \leq M \cdot \max_{t<0} |\delta_{t+1} - \delta_t|$$

Here δ is a vector of differential trends for the pre- and post-period. Note that this is complicated by the fact that data are not available for 2020 and 2021; for $t = 2019$, I treat $t + 1 = 2022$. In

32. Gerardo Silva-Padron and Meghan McCann, *50-State Comparison: Instructional Time Policies*, February 6, 2023, accessed March 17, 2024, https://www.ecs.org/50-state-comparison-instructional-time-policies-2023/.

33. Ashesh Rambachan and Jonathan Roth, "A More Credible Approach to Parallel Trends," *Review of Economic Studies* 90, no. 5 (September 5, 2023): 2555–2591, ISSN: 0034-6527, 1467-937X, accessed March 9, 2025, https://doi.org/10.1093/restud/rdad018, https://academic.oup.com/restud/article/90/5/2555/7039335.

regression tables throughout, I indicate results robust to a deviation from parallel trends defined by $M = 2$ in bold.

I begin by verifying findings mentioned in the introduction, using Data Set A. I use a difference-in-differences model to explore the change in test score gaps from 2019 to 2022:[34]

$$score_{d,s,t} = \beta_1 year22_t + \beta_2 year22_t \times pctecd_d + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,s,t} \tag{1}$$

$$score_{d,s,t} = \beta_1 year22_t + \beta_2 year22_t \times pctblk_d + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,s,t} \tag{2}$$

$$score_{d,s,t} = \beta_1 year22_t + \beta_2 year22_t \times pcthsp_d + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,s,t} \tag{3}$$

where $score_{d,s,t}$ is the average standardized score in district d in year t in state s, $year22_t$ is a dummy variable that equals 1 for observations from 2022, and $pctecd_d$, $pctblk_d$, $pcthsp_d$ represent the percent of students in district d who are economically disadvantaged, Black, or Hispanic, respectively. α_d are district fixed effects.

In these equations, a significant negative value of β_2 is evidence that districts with a higher percentage of students within the relevant subgroup are performing worse in 2022 than in 2019.

I use a triple difference (DDD) estimator as introduced by Gruber[35] to estimate the effect of in-person learning on the change in district test score gaps.

$$\begin{aligned} score_{d,s,t} =& \beta_1 year22_t + \beta_2 pctecd_d + \beta_3 inperson_d + \beta_4 year22_t \times pctecd_d + \beta_5 year22_t \times inperson_d \\ &+ \beta_6 pctecd_d \times inperson_d + \beta_7 year22_t \times pctecd_d \times inperson_d + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,s,t} \end{aligned} \tag{4}$$

where variables are defined as above and $inperson_d$ takes values in $[0, 1]$ and represents the percentage of the 2020–2021 school year that district d was fully in-person.

Here β_7 is a DDD estimator representing the difference in the change in test score gaps between districts based on whether schools were in person. A positive value would indicate that economically disadvantaged school districts that spent more of the 2020–2021 school year in person lost less ground

34. Throughout this section, I write equations using "score" as the dependent variable. Since I am examining both mathematics and reading/language arts scores, each equation represents two regressions: one using math scores as the dependent variable and the other using reading/language arts scores. To avoid redundancy, I provide general equations. Separate regressions are shown in the results section.

35. Jonathan Gruber, "The Incidence of Mandated Maternity Benefits," Publisher: American Economic Association, *The American Economic Review* 84, no. 3 (1994): 622–641, ISSN: 0002-8282, accessed March 16, 2024, https://www.jstor.org/stable/2118071.

than similar districts that spent more time in remote or hybrid learning.

I use similar models on Data Set B to explore trends through Spring 2023:

$$score_{d,s,t} = \beta_1 year_t + \beta_2 pctecd_d + \beta_3 year_t \times pctecd_d + \alpha_s + \epsilon_{d,s,t} \tag{5}$$

$$\begin{aligned} score_{d,s,t} =& \beta_1 year_t + \beta_2 pctecd_d + \beta_3 inperson_d + \beta_4 year_t \times pctecd_d + \beta_5 year_t \times inperson_d \\ &+ \beta_6 pctecd_d \times inperson_d + \beta_7 year22_t \times pctecd_d \times inperson_d + \alpha_s + \epsilon_{d,s,t} \end{aligned} \tag{6}$$

Here $year_t$ has 3 levels: 2019 (base year), 2022, and 2023. Regression output shows different coefficients for 2022, 2023, and interactions with both years. I simplify the remainder of this section by writing one equation to represent models including and excluding 2023 data as the equations are analogous.

3.2 Subgroup Analysis

Data from SEDA include average scores for racial and socioeconomic subgroups. I use these averages to examine score gaps at the subgroup level. I explore several different subgroups and provide similar analysis for each. First, I examine the growth in score gaps from 2019 to 2022 of the form

$$score_{d,g,s,t} = \beta_1 year_t + \beta_2 grp_g + \beta_3 year_t \times grp_g + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,g,s,t} \tag{7}$$

and the analogous equations for Black and Hispanic percentages where $score_{d,g,s,t}$ is the average standardized score in district i in year t for subgroup g and grp_g is a dummy variable equal to 1 for observations in the subgroup of interest (g).

Thus, β_3 is an estimate of the change in a test score gap from 2019 to 2022.

I fit the model:

$$\begin{aligned} score_{d,g,s,t} =& \beta_1 year_t + \beta_2 grp_g + \beta_3 inperson_d + \beta_4 year_t \times grp_g + \beta_5 year_t \times inperson_d \\ &+ \beta_6 grp_g \times inperson_d + \beta_7 year_t \times grp_g \times inperson_d + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,g,s,t} \end{aligned} \tag{8}$$

As above, β_7 is a DDD estimator representing the difference in the change in test score gaps based on the percentage of the year schools were in person.

I also provide a fully interacted model including average COVID deaths within each district and a fully interacted model including the difference between the average district-wide score in 2019 and the average district-wide score in 2018 (separated by subgroup). I refer to the latter as pre-trends because I use it to test whether trends before the pandemic can explain the difference in trends during and after the school closures. These models are included to check the robustness of the model in equation (8).

Finally, I explore a DDD model with year, subgroup, modality, and percent of district economically disadvantaged. This model can provide insight into the mechanisms behind test score gaps. If economically disadvantaged districts and students are performing worse, optimal policy response depends on whether the trend is occurring mostly at the district level or the individual level. The regression equation is below:

$$\begin{aligned} score_{d,g,s,t} =& \beta_1 year_t + \beta_2 grp_g + \beta_3 pctecd_d + \beta_4 year_t \times grp_g + \beta_5 year_t \times pctecd_d \\ &+ \beta_6 grp_g \times pctecd_d + \beta_7 year_t \times grp_g \times pctecd_d + \delta state_s \times year22_t + \alpha_d + \epsilon_{d,g,s,t} \end{aligned} \tag{9}$$

A negative coefficient on β_4 suggests that the effect is on an individual level–regardless of the average socioeconomic status of the school district, children in that subgroup are doing worse after the pandemic. A negative coefficient on β_6 suggests that the effect is larger at the district level–disadvantaged districts as a whole have been performing worse, which can explain the differences between subgroup means. The interaction term β_7 can provide insight into how disadvantaged students are performing in disadvantaged districts.

4 Results

4.1 District-Level Effects

Consistent with E. M. Fahle et al.,[36] I find that school districts with a higher share of economically disadvantaged students saw significantly larger learning loss. Furthermore, this newly created gap has not closed from 2022 to 2023. The basic model (see Table 1 columns (1) and (2)) shows no evidence that school districts with few economically disadvantaged students experienced any learning

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loss in reading. There is evidence that math scores fell regardless of district demographics, but this impact appears to be short-term, with near full recovery by 2023. However, for school districts with a high share of economically disadvantaged students, the drop in test scores was much more extreme in both math and reading. This gap is persistent; while less disadvantaged school districts have recovered, economically disadvantaged school districts are still far behind pre-COVID achievement levels. It appears that the gap in math scores has shrunk slightly, while the gap in reading scores has not.

Figure 1 shows the difference in average scores from the 2019 level for 2016 through 2023. The data have been split into quartiles based on the percentage of the student body that is economically disadvantaged. The plot shows that all quartiles had similar trends prior to the onset of the pandemic, but districts with more economically disadvantaged students saw a greater drop in scores from 2019 to 2022. Although all quartiles show evidence of recovery from 2022 to 2023, the new gap between low-poverty and high-poverty schools did not close. Note that this plot obscures the score gap that existed before the pandemic.

Columns (3) and (4) of Table 1 show a regression of test scores on modality. I find evidence that schools districts that spent more of the 2020–2021 school year in person had higher average math and reading scores in both 2022 and 2023. The overall effect of in-person learning was larger for math scores than reading scores. Although, as seen in Figure C6, trends leading up to the pandemic are not parallel, the finding is robust to this difference in parallel trends in math scores, using methods of Rambachan and Roth. Columns (5) and (6) show district economic demographics interacted with the percentage of the 2020–2021 school year a district spent in person. This interaction reveals that in-person learning had a unique positive effect for economically disadvantaged school districts' math scores, but I find no unique effect on reading scores. The difference in the drop in math scores between low- and high-poverty school districts is larger for schools that spent less time in person. Figure C7 shows trends in scores by the share of a school district that is economically disadvantaged. Separate graphs are provided to show trends in schools that were never in person in the 2020–2021 school year and fully in-person schools. There are differential trends for schools that would be fully in-person, so this estimate is not robust with respect to the methods described above.

Table 2 shows similar regressions but examines the racial demographics of schools (and excludes the regression focused solely on modality).

Columns (1) and (2) show that districts with a higher percentage of Black students saw larger

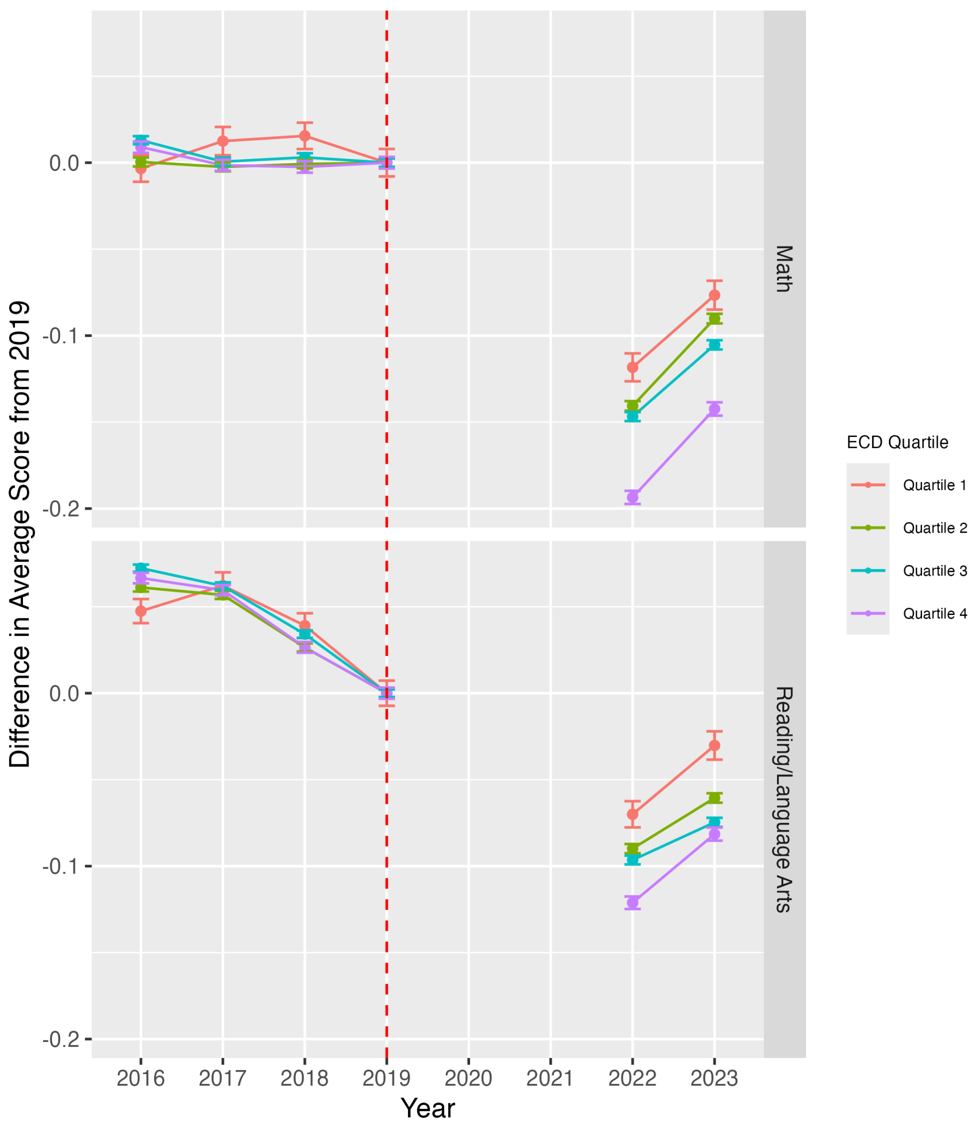

Figure 1: Average Scores By Subject and Percent of Students in District Classified as Economically Disadvantaged (Quartile) – Data Set B

Table 1: DD Regression of Score on Percent of District ECD (2023 Included) - Base Year 2019

	Dependent variable:					
	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)
2022	−0.029***	−0.001	−0.179***	−0.097***	−0.064***	−0.018***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
2023	−0.008	0.012**	−0.133***	−0.084***	−0.034***	−0.004
	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
2022 × % ECD	**−0.164***	**−0.117***			**−0.173***	−0.112***
	(0.007)	(0.006)			(0.008)	(0.007)
2023 × % ECD	**−0.142***	**−0.121***			**−0.150***	−0.111***
	(0.007)	(0.006)			(0.008)	(0.007)
2022 × In Person			**0.079***	0.036***	0.028***	0.029***
			(0.005)	(0.005)	(0.011)	(0.010)
2023 × In Person			**0.061***	0.032***	0.017	0.034***
			(0.005)	(0.005)	(0.011)	(0.010)
2022 × % ECD × In Person					0.075***	−0.006
					(0.018)	(0.016)
2023 × % ECD × In Person					0.064***	−0.024
					(0.018)	(0.017)
Observations	10,302	10,302	10,302	10,302	10,302	10,302
R^2	0.522	0.481	0.519	0.467	0.535	0.485
Adjusted R^2	0.278	0.217	0.273	0.195	0.297	0.222
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2: DD Regression of Score on Percent of District Black and Hispanic on (2023 Included) - Base Year 2019

	Dependent variable:							
	Math	RLA	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2022	−0.054***	−0.032***	−0.107***	−0.064***	−0.087***	−0.045***	−0.147***	−0.082***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
2023	−0.039***	−0.029***	−0.071***	−0.052***	−0.066***	−0.042***	−0.100***	−0.067***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
2022 × % Black	**−0.227***	**−0.126***			**−0.202***	−0.104***		
	(0.008)	(0.008)			(0.010)	(0.009)		
2023 × % Black	**−0.170***	**−0.105***			**−0.139***	−0.072***		
	(0.008)	(0.008)			(0.010)	(0.010)		
2022 × % Hispanic			**−0.173***	−0.081***			**−0.162***	−0.074***
			(0.010)	(0.009)			(0.012)	(0.011)
2023 × % Hispanic			**−0.176***	−0.092***			**−0.164***	−0.075***
			(0.010)	(0.009)			(0.012)	(0.011)
2022 × In Person					0.050***	0.026***	**0.061***	0.029***
					(0.006)	(0.006)	(0.006)	(0.006)
2023 × In Person					0.046***	0.032***	**0.047***	0.032***
					(0.006)	(0.006)	(0.006)	(0.006)
2022 × % Black × In Person					−0.015	−0.055***		
					(0.021)	(0.019)		
2023 × % Black × In Person					−0.052**	−0.098***		
					(0.021)	(0.020)		
2022 × % Hispanic × In Person							0.066*	0.013
							(0.036)	(0.033)
2023 × % Hispanic × In Person							0.019	−0.061*
							(0.036)	(0.033)
Observations	10,302	10,302	10,302	10,302	10,302	10,302	10,302	10,302
R^2	0.527	0.472	0.522	0.468	0.533	0.475	0.532	0.472
Adjusted R^2	0.285	0.203	0.278	0.197	0.295	0.207	0.293	0.202
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:								*p<0.1; **p<0.05; ***p<0.01

drops in both math and reading scores than districts with fewer Black students. The gap has shrunk from 2022 to 2023, but as of 2023, there was still a significantly larger gap than in 2019. Similarly, columns (3) and (4) show that districts with a higher percentage of Hispanic students have also seen larger drops in reading and math scores. Here, I do not find evidence that the gap is closing.

Examining the interactions of racial demographics with teaching modality confirms that school districts that spent more of the 2020–2021 school year in person saw a smaller drop in average math and reading scores. Columns (5) and (6) show the interaction between the percentage of the school district that is Black and teaching modality. I find evidence that school districts with more Black students saw smaller gains associated with in-person learning. In 2022, districts with a high percentage of Black students that spent more of the 2020–2021 school year in person had lower average reading scores than those that spent less time in person. Looking at 2023 test scores, this gap has only grown. In 2022, there was no noticeable difference in math scores between modalities within majority-Black school districts. By 2023, a significant gap appeared, with in-person school districts again performing relatively worse. Another way to interpret this is that, among schools that spent more of the 2020–2021 school year in person, those with a higher share of Black students saw lower returns to in-person learning, with returns perhaps even negative in the long run.

As shown in Figures C8 and C9, trends leading up to 2019 are not parallel, so these results should not be interpreted as causal. Accordingly, the findings are not robust to a violation in parallel trends. However, the fact that the estimates are increasing in magnitude suggests that this trend warrants further investigation. In particular, among fully in-person school districts (top panel of C9), districts in "Quartile 1" (i.e., districts with the fewest Hispanic students) saw a much greater recovery from 2022 to 2023 than other districts.

4.2 Subgroup Analysis: Economically Disadvantaged

Analysis of scores by socioeconomic status (using data set D) shows a relatively small growth in the math test score gap within school districts from 2019 to 2022 and only weak evidence of growth in a reading score gap (see Table 3, columns (1) & (2)). This lack of a score gap contrasts with the much larger growth in test score gaps between districts, suggesting that the effect of the pandemic acted at the district level, rather than the individual level. Figure 2 shows score trends from 2016 to 2023 for both subgroups. The figure shows that, while the initial drop in scores was similar for both subgroups, scores of higher income students increased more from 2022 to 2023 than scores

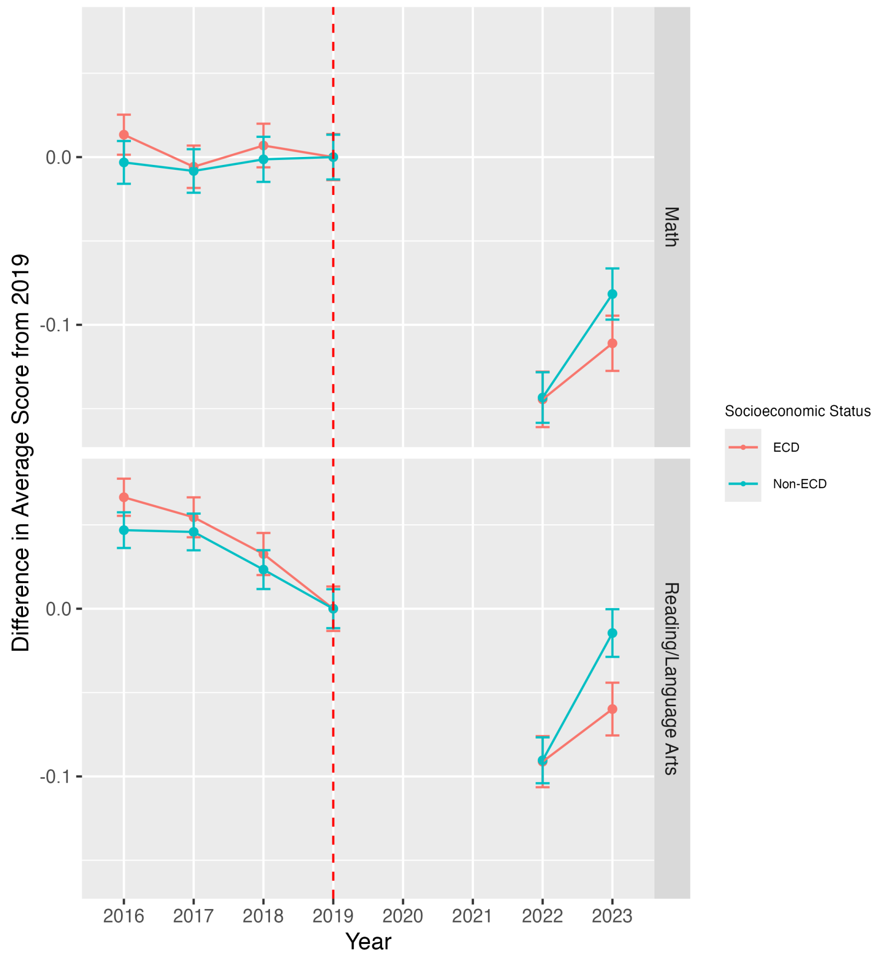

Figure 2: Average Scores By Subject and Socioeconomic Status – Data Set D

of economically disadvantaged students. Table 3 also shows this, with the negative value on the interaction term for year and economically disadvantaged larger in magnitude for 2023 than 2022. Overall, this is evidence of an unequal recovery, where economically disadvantaged students are not recovering from the pandemic learning loss as quickly as their higher income classmates.

The DDD regression (Table 3, columns (3) & (4)) does not provide evidence for differential returns to in-person learning by socioeconomic status. However, there is evidence that in-person learning during the 2020–2021 school year is associated with higher scores, at least for higher income students.

Columns (5) and (6) of Table 3 include the average COVID-19 death rate over the 2020–2021 school year. Schools in counties with more COVID-19 deaths saw a larger drop in average reading

Table 3: Regression of Scores on Socioeconomic Status (2023 Included) - Base Year 2019

	Dependent variable:					
	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)
2022	−0.102***	−0.065***	−0.117***	−0.074***	−0.117***	−0.081***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
2023	−0.071***	0.072***	−0.081***	0.064***	−0.084***	0.054***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
ECD	−0.591***	−0.573***	−0.603***	−0.586***	−0.565***	−0.555***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
2022 × ECD	−0.017**	−0.017**	−0.011	−0.009	−0.009	−0.003
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)
2023 × ECD	−0.035***	−0.043***	−0.033***	−0.035***	−0.026***	−0.023**
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)
2022 × In Person			0.085***	0.045***	0.085***	0.053***
			(0.017)	(0.016)	(0.017)	(0.016)
2023 × In Person			0.061***	0.039**	0.065***	0.051***
			(0.017)	(0.016)	(0.017)	(0.016)
ECD × In Person			0.049***	0.056***	−0.002	0.014
			(0.016)	(0.015)	(0.016)	(0.015)
2022 × COVID					0.001	−0.015**
					(0.008)	(0.007)
2023 × COVID					−0.002	−0.020***
					(0.008)	(0.007)
ECD × COVID					0.095***	0.083***
					(0.007)	(0.007)
2022 × ECD × In Person			−0.022	−0.032	−0.024	−0.038*
			(0.023)	(0.022)	(0.023)	(0.022)
2023 × ECD × In Person			−0.004	−0.034	−0.016	−0.052**
			(0.023)	(0.022)	(0.023)	(0.022)
2022 × ECD × COVID					−0.0003	0.004
					(0.010)	(0.010)
2023 × ECD × In Person					0.012	0.022**
					(0.010)	(0.010)
2022 × In Person × COVID					−0.014	0.002
					(0.018)	(0.017)
2023 × In Person × COVID					−0.014	0.004
					(0.018)	(0.017)
ECD × In Person × COVID					−0.088***	−0.076***
					(0.018)	(0.017)
2022 × ECD × In Person × COVID					0.014	0.007
					(0.025)	(0.024)
2023 × ECD × In Person × COVID					0.020	0.003
					(0.025)	(0.024)
Observations	9,414	9,414	9,414	9,414	9,414	9,414
R^2	0.860	0.867	0.861	0.867	0.862	0.867
Adjusted R^2	0.831	0.840	0.832	0.840	0.834	0.839
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

scores but no change in average math scores. Furthermore, controlling for COVID-19 deaths reveals a negative interaction between the economically disadvantaged subgroup and in-person modality on reading scores, most significant in 2023 (see the row labeled 2023 $\times$ ECD $\times$ In Person). This contrasts with the finding shown in Table 1, that districts with a higher percentage of economically disadvantaged students had a positive relationship between in-person learning and math scores. In-person learning appears to have reduced the growth in inequality in math scores but may have widened gaps in reading scores. Due to violations in parallel trends, neither of these findings can be interpreted as causal. Finally, the model with COVID deaths suggests that the effect of in-person learning cannot be explained by death rates, nor can the slower recovery of economically disadvantaged students.

To check whether results are due to pre-COVID trends, I include a model with the change in score from 2018 to 2019 fully interacted in Table B5. The results are similar, suggesting that these post-COVID trends cannot be explained by districts' pre-COVID trends. Despite this, analysis based on Rambachan and Roth shows a lack of robustness, so these results should be interpreted with caution.

Table B3 shows the regressions discussed above using data set C and excluding 2023 test score data. This makes use of a larger data set and shows similar results, suggesting that the results are not due to a biased sample.

Table 4 shows the regression with individual socioeconomic status and district socioeconomic status specified in Equation 9. This demonstrates that, on average, students in districts with a high percentage of economically disadvantaged students performed worse in all years, regardless of their own economic status. Conversely, controlling for the demographics of a school district, it still appears that economically disadvantaged students are falling behind in the recovery from 2022 to 2023. This finding is robust to a violation of parallel trends. The coefficient on the interaction term between individual SES and district SES is positive, although this finding is less robust. These scores are standardized, meaning group averages can only reasonably get so far from zero; this positive interaction may be partially due to this. There is good evidence that, in 2023, the COVID-related SES score gap is smaller in districts with more economically disadvantaged students. Essentially, the pandemic caused a disproportionate drop in test scores in high-poverty school districts from 2019 to 2022, which continued into 2023. These effects were felt relatively equally among all students in these school districts. Furthermore, in low-poverty school districts, economically disadvantaged students

Table 4: DDD Regression for Interaction of ECD and Percent of District ECD - Base Year 2019

	Dependent variable:	
	Math	RLA
	(1)	(2)
2022	-0.031^{**}	0.006
	(0.013)	(0.012)
2023	0.006	0.156^{***}
	(0.013)	(0.012)
ECD	-0.746^{***}	-0.636^{***}
	(0.012)	(0.012)
2022 × ECD	0.017	-0.014
	(0.018)	(0.018)
2023 × ECD	-0.045^{**}	-0.097^{***}
	(0.018)	(0.018)
2022 × % District ECD	$\mathbf{-0.186}^{***}$	$\mathbf{-0.188}^{***}$
	(0.024)	(0.023)
2023 × % District ECD	$\mathbf{-0.201}^{***}$	$\mathbf{-0.225}^{***}$
	(0.024)	(0.024)
ECD × % District ECD	0.286^{***}	0.098^{***}
	(0.023)	(0.023)
2022 × ECD × % District ECD	-0.009	0.048
	(0.034)	(0.034)
2023 × ECD × % District ECD	0.075^{**}	0.160^{***}
	(0.034)	(0.034)
Observations	9,414	9,414
R^2	0.874	0.874
Adjusted R^2	0.848	0.849
District Fixed Effects	Yes	Yes
State-Year Dummies	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

have seen less recovery in test scores from 2022 to 2023. This trend does not hold in high-poverty school districts.

Table B4 shows the same regression (specified in Equation 9) using data set C (and thus excluding 2023). The positive coefficient on the interaction term between 2022 and the ECD subgroup for math scores suggests that, during the pandemic, economically disadvantaged students actually gained ground in low-poverty districts. The negative DDD term suggests that this trend did not hold to the same degree in high-poverty districts. Since the data are not nationally representative, these results should be interpreted with some skepticism, but they support the conclusion that students in high-poverty schools were most affected by the pandemic, regardless of their own socioeconomic status. This is consistent with the findings of E. M. Fahle et al.,[37] that the mechanisms that drove learning loss affected students within a district to a similar degree, regardless of each individual student's background.

4.3 Subgroup Analysis: Race

A DD regression with race as subgroups as in equation (7) is shown in columns (1) and (2) of Table 5 (using data set E). I find no significant growth in the Black-white test score gap from 2019 to 2022, but the white-Hispanic score gap grew in both math and reading. This is not robust to differential pre-trends. Figure C5 shows score trends from 2016 to 2023 for all three subgroups. The DDD regression specified in equation (9) shows no evidence of differential returns to in-person learning by race. When modality interaction terms are added, the growth in the white-Hispanic gap is no longer significant at the 95% level. Columns (5) and (6) include COVID-19 death rates and, similarly to their inclusion in the SES regressions, do not significantly alter the results.

Table B6 shows columns (1)-(4) using data set F and including 2023 scores. Like non-ECD students, white students have recovered significantly from 2022 to 2023, at least in reading scores. There is also notable growth in the white-Hispanic score gap that does not shrink from 2022 to 2023. There are no significant interactions with modality. The uneven recovery can also be seen in Figure C5. While trends are similar before 2020, Hispanic students saw the largest drop in test scores in both reading and math and are still further behind 2019 levels than Black or white students. Table B8 includes the difference in 2019 and 2018 scores by district (pre-trends). The interactions with

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the pre-trends are not significant, suggesting previous trends within school districts do not explain my results.

Interactions between race and the percent of the district that is economically disadvantaged are shown in table B7. The interaction terms are not significant in 2022 or 2023.

Table 5: Regressions of Score on Race - Base Year 2019

	Dependent variable:					
	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)
2022	-0.103^{***}	-0.034	-0.111^{***}	-0.038	-0.112^{***}	-0.041
	(0.030)	(0.032)	(0.031)	(0.033)	(0.030)	(0.032)
Black	-0.777^{***}	-0.725^{***}	-0.812^{***}	-0.750^{***}	-0.790^{***}	-0.731^{***}
	(0.013)	(0.013)	(0.017)	(0.017)	(0.017)	(0.017)
Hispanic	-0.520^{***}	-0.567^{***}	-0.545^{***}	-0.586^{***}	-0.505^{***}	-0.544^{***}
	(0.012)	(0.013)	(0.017)	(0.018)	(0.017)	(0.018)
2022 × Black	-0.028	-0.013	-0.012	-0.005	-0.009	-0.004
	(0.019)	(0.019)	(0.024)	(0.026)	(0.024)	(0.026)
2022 × Hispanic	-0.047^{**}	-0.042^{**}	-0.043^{*}	-0.037	-0.040	-0.036
	(0.018)	(0.019)	(0.025)	(0.026)	(0.026)	(0.027)
2022 × In Person			0.060	0.028	0.063	0.036
			(0.041)	(0.043)	(0.039)	(0.041)
Black × In Person			0.128^{***}	0.091^{**}	0.100^{**}	0.066
			(0.041)	(0.043)	(0.040)	(0.043)
Hispanic × In Person			0.078^{**}	0.062	0.027	0.008
			(0.039)	(0.041)	(0.038)	(0.041)
2022 × COVID					-0.006	-0.015
					(0.018)	(0.019)
Black × COVID					0.090^{***}	0.073^{***}
					(0.019)	(0.020)
Hispanic × COVID					0.148^{***}	0.154^{***}
					(0.021)	(0.023)
2022 × Black × In-Person			-0.053	-0.027	-0.058	-0.029
			(0.061)	(0.064)	(0.059)	(0.063)
2022 × Hispanic × In-Person			-0.010	-0.013	-0.011	-0.015
			(0.057)	(0.059)	(0.056)	(0.060)
2022 × Black × COVID					0.012	0.004
					(0.028)	(0.030)
2022 × Hispanic × COVID					0.009	0.008
					(0.031)	(0.033)
2022 × In-Person × COVID					0.010	0.033
					(0.038)	(0.040)
Black × In-Person × COVID					-0.054	-0.065
					(0.043)	(0.046)
Hispanic × In-Person × COVID					-0.109^{***}	-0.122^{***}
					(0.042)	(0.045)
2022 × Black × In-Person × COVID					-0.020	-0.010
					(0.064)	(0.067)
2022 × Hispanic × In-Person × COVID					-0.001	-0.020
					(0.062)	(0.066)
Observations	1,488	1,488	1,488	1,488	1,488	1,488
R^2	0.854	0.834	0.855	0.833	0.865	0.842
Adjusted R^2	0.823	0.797	0.823	0.796	0.833	0.804
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

5 Discussion

My findings suggest that the growth in test score gaps from 2019 to 2022 is largely attributable to district-level differences; growth in gaps between high-poverty and low-poverty schools is more pronounced than growth in gaps between economically disadvantaged students and higher income students. This growth in score gaps is larger in math than in reading. Results regarding race and ethnicity (Black and Hispanic) are similar; districts with more Black or Hispanic students saw a larger drop in test scores from 2019 to 2022 and this unequal drop has persisted into 2023.

Recall that E. M. Fahle et al.[38] and Goldhaber et al.[39] both find that high-poverty districts were more affected by remote and hybrid learning. My findings support this claim and suggest that the effect is stronger on math scores than on reading scores. I extend this analysis to 2023 test scores and find that high-poverty districts that spent more of the 2020–2021 school year in-person still have higher math scores than high-poverty districts that were remote or hybrid. Despite this equalizing effect of in-person learning, I find evidence that school districts with more Black students saw a smaller effect of in-person learning and perhaps even a negative impact on reading scores. This is unexpected and difficult to explain, so more research should be done to draw accurate conclusions from this finding. This result could also be due to differential trends before the pandemic. Overall, in-person instruction in 2020–2021 appears to have supported math learning more than reading learning. To the extent that in-person instruction uniquely helped disadvantaged school districts, the impact was on math scores.

This does not constitute an argument that schools should have been reopened sooner. There is reason to believe[40] that school reopenings led to an increase in COVID transmission.[41,42,43] Rather,

38. E. M. Fahle et al., *School District and Community Factors Associated With Learning Loss During the COVID-19 Pandemic.*

39. Goldhaber et al., "The Consequences of Remote and Hybrid Instruction During the Pandemic."

40. Isphording, Lipfert, and Pestel ("Does re-opening schools contribute to the spread of SARS-CoV-2?") find no association between schools reopening and increased transmission rates in Germany. This paper does not attempt to evaluate the conflicting results.

41. Emanuele Amodio et al., "Schools opening and Covid-19 diffusion: Evidence from geolocalized microdata," *European Economic Review* 143 (April 2022): 104003, ISSN: 0014-2921, https://doi.org/10.1016/j.euroecorev.2021.104003.

42. Victor Chernozhukov, Hiroyuki Kasahara, and Paul Schrimpf, "The association of opening K–12 schools with the spread of COVID-19 in the United States: County-level panel data analysis," *Proceedings of the National Academy of Sciences of the United States of America* 118, no. 42 (October 19, 2021): e2103420118, ISSN: 0027-8424, accessed March 19, 2024, https://doi.org/10.1073/pnas.2103420118, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8545468/.

43. Dan Goldhaber et al., "To What Extent Does In-Person Schooling Contribute to the Spread of COVID-19? Evidence from Michigan and Washington," National Center for Analysis of Longitudinal Data in Education Research, July 2021, accessed March 19, 2024, https://caldercenter.org/sites/default/files/CALDER%20WP%20247-1220-3.pdf.

cogent analysis requires consideration of all aspects of a policy; this paper contributes to the larger discussion by addressing the specific areas of learning loss and test score gaps.

Overall, my results suggest that high-poverty districts were harmed more by the pandemic than low-poverty districts. Low-poverty districts had the most noticeable and consistent drop in test scores and there is no indication that the gap has been closing. Furthermore, economically disadvantaged students in low- or mid-poverty school districts have seen slower recovery from 2022 to 2023 than their peers. Thus, the effect of the pandemic on education can be split into two main periods: the initial drop (2019–2022) where high-poverty and high-minority school districts saw a larger drop in test scores than low-poverty or majority-white districts, and the recovery (2022–2023) where high-poverty and high-minority districts are still lagging behind and, additionally, economically disadvantaged students in more advantaged school districts are experiencing slower recovery than their peers.

The present paper uses school districts as the smallest unit of analysis. This obscures the important differences between schools within a school district and children within a school. More analysis at the school level could help determine where inequalities are growing. Analysis using panel data could also be insightful.

Another limitation is that test score data were averaged across all students in grades 3 through 8. It is reasonable to believe that school closures and other aspects of the pandemic affected children in 3rd grade differently than those in 8th grade. Furthermore, analysis by gender could potentially show interesting differences. While this analysis highlights important trends, analysis with more specific subgroups could be compelling.

Alternatively, access to more data would improve this analysis. As seen in the sample composition tables, my analysis included test scores from millions of students, but there are many states, school districts, and students missing. While this analysis suggests national trends, a nationally representative study would be ideal.

Future research should examine how districts can address these inequalities. Specifically, it would be useful to see how much funding is needed to close score gaps and how that funding should be allocated in order to be most effective. During the pandemic, the American Rescue Plan Elementary and Secondary School Emergency Relief Fund allocated 122 billion dollars to state education agencies. Halloran et al.[44] find no correlation between this spending and recovery, but

44. Halloran et al., *Post COVID-19 Test Score Recovery.*

they note that impacts may not be visible yet.

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Appendicies

A: Sample Composition

- Data Set A (all, 2022): Averages of all scores within a school district; scores reported in 2016, 2017, 2018, 2019, 2022
- Data Set B (all, 2023): Averages of all scores within a school district; scores reported in 2016, 2017, 2018, 2019, 2022, 2023
- Data Set C (ECD, 2022): Averages of scores within a school district by ECD and non-ECD subgroups; scores reported in 2016, 2017, 2018, 2019, 2022
- Data Set D (ECD, 2023): Averages of scores within a school district by ECD and non-ECD subgroups; scores reported in 2016, 2017, 2018, 2019, 2022, 2023
- Data Set E (Race, 2022): Averages of scores within a school district by Black, Hispanic, and white subgroups; scores reported in 2016, 2017, 2018, 2019, 2022
- Data Set F (Race, 2023): Averages of scores within a school district by Black, Hispanic, and white subgroups; scores reported in 2016, 2017, 2018, 2019, 2022, 2023

Table A1: Data Set A – Sample Composition by State

State	Districts	Number of Students			
		2019		2022	
		Math	RLA	Math	RLA
Florida	64	837,006	1,264,236	792,701	1,229,126
Georgia	164	782,700	779,009	745,115	745,858
Idaho	57	122,868	122,422	118,970	118,864
Illinois	417	738,285	765,651	714,330	714,364
Indiana	244	426,647	424,350	414,707	414,964
Kansas	129	190,875	190,274	188,001	187,979
Kentucky	144	296,259	295,221	277,588	278,466
Louisiana	61	274,381	274,906	251,754	246,455
Massachusetts	194	344,904	344,665	335,257	335,409
Michigan	353	520,921	519,274	472,381	476,017
Minnesota	200	322,248	326,736	305,968	307,381
Mississippi	125	207,340	207,604	186,940	187,178
Missouri	191	291,146	346,999	273,131	328,803
Nebraska	72	119,516	119,578	118,798	118,894
Nevada	11	200,993	201,221	179,698	180,102
New Hampshire	53	46,599	46,351	46,753	47,125
New Jersey	210	336,018	393,624	313,660	377,460
North Carolina	111	661,956	662,405	618,799	619,556
North Dakota	7	26,658	26,538	27,040	26,972
Ohio	330	351,529	527,516	322,407	498,933
Oklahoma	74	192,772	193,388	178,860	176,904
Pennsylvania	377	511,395	503,696	494,617	494,642
Rhode Island	28	56,361	55,436	50,879	51,208
South Carolina	70	338,434	338,550	322,731	322,543
South Dakota	45	48,645	48,759	47,599	47,480
Texas	369	1,412,248	1,418,672	1,303,275	1,362,553
Utah	31	228,412	229,328	229,349	229,353
Washington	89	216,495	218,066	206,354	206,808
Wisconsin	244	307,670	306,714	278,239	278,082
Wyoming	35	42,073	42,014	40,449	40,450

Table A2: Data Set B – Sample Composition by State

State	Districts	Number of Students					
		2019		2022		2023	
		Math	RLA	Math	RLA	Math	RLA
Georgia	164	782,700	779,009	745,115	745,858	741,858	742,589
Illinois	417	738,285	765,651	714,330	714,364	723,069	723,328
Indiana	244	426,647	424,350	414,707	414,964	412,640	412,817
Kansas	129	190,875	190,274	188,001	187,979	189,241	189,272
Kentucky	144	296,259	295,221	277,588	278,466	277,763	279,081
Louisiana	61	274,381	274,906	251,754	246,455	253,642	253,684
Massachusetts	194	344,904	344,665	335,257	335,409	332,859	332,728
Michigan	353	520,921	519,274	472,381	476,017	478,809	478,247
Mississippi	125	207,340	207,604	186,940	187,178	180,366	180,525
Nevada	11	200,993	201,221	179,698	180,102	177,889	178,306
New Hampshire	53	46,599	46,351	46,753	47,125	48,270	48,293
New Jersey	210	336,018	393,624	313,660	377,460	312,491	374,362
North Carolina	111	661,956	662,405	618,799	619,556	614,020	614,344
Ohio	330	351,529	527,516	322,407	498,933	321,097	487,075
Oklahoma	74	192,772	193,388	178,860	176,904	180,408	174,527
Pennsylvania	377	511,395	503,696	494,617	494,642	503,140	502,308
Rhode Island	28	56,361	55,436	50,879	51,208	49,702	50,015
South Dakota	45	48,645	48,759	47,599	47,480	47,649	47,480
Utah	31	228,412	229,328	229,349	229,353	235,369	235,372
Washington	89	216,495	218,066	206,354	206,808	207,148	207,258
Wisconsin	244	307,670	306,714	278,239	278,082	276,536	276,295

Table A3: Data Set C – Sample Composition by State

State	Districts	Number of Students							
		2019: Math		2019: RLA		2022: Math		2022: RLA	
		ECD	Non-ECD	ECD	Non-ECD	ECD	Non-ECD	ECD	Non-ECD
Idaho	14	25,832	36,073	25,725	36,078	12,485	42,343	13,306	45,626
Illinois	307	233,062	296,792	234,068	297,596	223,504	278,715	223,598	278,885
Kentucky	127	177,758	110,481	177,085	110,108	153,469	113,846	156,425	114,236
Louisiana	54	185,756	79,404	186,289	79,408	134,199	106,314	131,746	102,788
Massachusetts	166	93,867	194,900	93,418	194,739	121,466	159,765	121,528	159,812
Michigan	284	207,372	251,799	207,070	250,688	198,474	220,584	200,359	220,853
Minnesota	161	109,219	196,720	111,728	198,668	87,943	201,585	88,470	202,393
Missouri	125	101,070	132,344	119,254	159,811	75,233	145,891	89,034	177,327
New Jersey	117	113,099	106,290	130,201	124,764	93,587	112,239	109,989	136,213
North Carolina	102	324,081	326,831	324,318	327,026	245,728	363,143	246,162	363,604
Ohio	173	88,274	124,633	128,603	193,603	73,674	125,078	110,185	198,505
South Carolina	68	209,459	128,092	209,370	128,195	198,223	123,684	198,049	123,670
South Dakota	23	14,970	26,102	14,733	26,335	11,522	27,701	11,525	28,102
Texas	283	838,305	509,424	815,644	535,925	744,818	485,520	762,548	519,095
Washington	38	46,024	53,189	46,624	53,944	47,945	50,995	48,142	51,053
Wisconsin	179	116,903	152,471	115,791	151,994	101,972	143,080	101,910	143,010
Wyoming	26	14,048	24,589	13,964	24,583	10,523	26,454	10,498	26,429

Table A4: Data Set D – Sample Composition by State

State	Districts	Number of Students					
		2019: Math		2019: RLA		2022: Math	
		ECD	Non-ECD	ECD	Non-ECD	ECD	Non-ECD
Illinois	307	233,062	296,792	234,068	297,596	223,504	278,715
Kentucky	127	177,758	110,481	177,085	110,108	153,469	113,846
Louisiana	54	185,756	79,404	186,289	79,408	134,199	106,314
Massachusetts	166	93,867	194,900	93,418	194,739	121,466	159,765
Michigan	283	206,471	251,434	206,170	250,322	197,600	220,241
New Jersey	117	113,099	106,290	130,201	124,764	93,587	112,239
North Carolina	102	324,081	326,831	324,318	327,026	245,728	363,143
Ohio	173	88,274	124,633	128,603	193,603	73,674	125,078
South Dakota	23	14,970	26,102	14,733	26,335	11,522	27,701
Washington	38	46,024	53,189	46,624	53,944	47,945	50,995
Wisconsin	179	116,903	152,471	115,791	151,994	101,972	143,080

State	Number of Students					
	2022: RLA		2023: Math		2023: RLA	
	ECD	Non-ECD	ECD	Non-ECD	ECD	Non-ECD
Illinois	223,598	278,885	220,512	285,733	220,369	285,711
Kentucky	156,425	114,236	154,409	113,556	157,097	114,123
Louisiana	131,746	102,788	160,867	87,045	160,352	85,407
Massachusetts	121,528	159,812	115,761	163,253	115,642	163,253
Michigan	199,490	220,510	200,651	222,397	200,120	221,868
New Jersey	109,989	136,213	102,497	102,666	119,466	125,042
North Carolina	246,162	363,604	324,569	279,743	324,889	279,894
Ohio	110,185	198,505	82,498	115,625	121,635	185,085
South Dakota	11,525	28,102	13,990	25,977	13,954	26,114
Washington	48,142	51,053	50,687	48,992	50,746	48,994
Wisconsin	101,910	143,010	101,823	141,781	101,682	141,719

Table A5: Data Set E – Sample Composition by State

State	Districts	Number of Students											
		2019: Math			2019: RLA			2022: Math			2022: RLA		
		Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic	White
Illinois	31	25,733	51,406	63,173	25,892	51,488	63,324	25,492	49,773	55,391	25,506	49,787	55,407
Kansas	7	11,108	20,865	34,882	11,083	19,467	34,923	10,148	20,416	32,739	10,143	20,417	32,734
Kentucky	4	22,173	10,392	39,404	22,029	10,047	39,384	21,463	10,791	35,073	21,458	10,794	35,073
Louisiana	13	42,904	8,659	66,188	42,915	8,704	66,206	39,483	10,870	57,654	39,047	10,958	57,149
Massachusetts	4	11,169	16,832	7,828	11,165	16,584	7,829	12,122	16,555	6,763	12,104	16,540	6,761
Michigan	9	10,193	6,704	38,290	10,140	6,641	38,234	8,826	6,273	33,482	9,094	6,203	33,454
Minnesota	17	20,860	14,489	58,183	23,179	15,214	59,090	20,932	14,067	51,154	21,090	14,207	51,410
Missouri	14	14,459	9,073	52,438	17,117	10,165	62,839	13,602	9,209	47,545	16,393	10,944	57,860
Nebraska	2	6,285	9,573	14,111	6,292	9,571	14,120	5,830	9,595	13,131	5,807	9,592	13,128
New Jersey	16	10,806	25,238	13,915	12,816	28,897	16,859	10,153	23,960	12,169	12,370	28,009	14,834
North Carolina	39	138,556	99,257	195,405	138,684	99,311	195,531	128,855	100,979	171,518	129,040	101,057	171,746
Ohio	4	17,136	5,503	10,900	24,588	8,060	15,907	15,046	5,290	9,217	22,053	8,078	13,660
South Carolina	32	86,887	33,220	144,399	86,849	33,219	144,382	80,459	36,567	134,156	80,346	36,548	134,153
South Dakota	1	1,370	1,409	6,860	1,341	1,167	6,857	1,327	1,537	6,407	1,309	1,506	6,400
Texas	52	120,514	339,772	177,389	121,057	335,039	179,000	111,689	307,660	157,392	117,531	318,430	162,013
Wisconsin	3	18,593	12,596	8,417	18,610	12,500	8,409	13,663	10,667	6,848	13,742	10,634	6,854

Table A6: Data Set F – Sample Composition by State

State	Districts	Number of Students								
		2019: Math			2019: RLA			2022: Math		
		Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic	White
Illinois	31	25,733	51,406	63,173	25,892	51,488	63,324	25,492	49,773	55,391
Kansas	7	11,108	20,865	34,882	11,083	19,467	34,923	10,148	20,416	32,739
Kentucky	4	22,173	10,392	39,404	22,029	10,047	39,384	21,463	10,791	35,073
Louisiana	13	42,904	8,659	66,188	42,915	8,704	66,206	39,483	10,870	57,654
Massachusetts	4	11,169	16,832	7,828	11,165	16,584	7,829	12,122	16,555	6,763
Michigan	9	10,193	6,704	38,290	10,140	6,641	38,234	8,826	6,273	33,482
New Jersey	16	10,806	25,238	13,915	12,816	28,897	16,859	10,153	23,960	12,169
North Carolina	39	138,556	99,257	195,405	138,684	99,311	195,531	128,855	100,979	171,518
Ohio	4	17,136	5,503	10,900	24,588	8,060	15,907	15,046	5,290	9,217
South Dakota	1	1,370	1,409	6,860	1,341	1,167	6,857	1,327	1,537	6,407
Wisconsin	3	18,593	12,596	8,417	18,610	12,500	8,409	13,663	10,667	6,848

State	Number of Students								
	2022: RLA			2023: Math			2023: RLA		
	Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic	White
Illinois	25,506	49,787	55,407	25,816	50,076	55,792	25,853	50,058	55,790
Kansas	10,143	20,417	32,734	10,249	20,542	32,949	10,265	20,536	32,952
Kentucky	21,458	10,794	35,073	21,540	10,845	35,179	21,543	10,844	35,179
Louisiana	39,047	10,958	57,149	39,444	11,313	57,485	40,555	11,346	57,782
Massachusetts	12,104	16,540	6,761	11,575	16,183	6,487	11,563	16,166	6,499
Michigan	9,094	6,203	33,454	9,387	6,450	33,779	9,365	6,334	33,676
New Jersey	12,370	28,009	14,834	9,643	24,261	11,725	11,902	27,992	14,259
North Carolina	129,040	101,057	171,746	126,425	102,458	167,301	126,474	102,500	167,372
Ohio	22,053	8,078	13,660	14,974	5,587	8,878	19,077	8,539	12,008
South Dakota	1,309	1,506	6,400	1,330	1,648	6,314	1,318	1,610	6,303
Wisconsin	13,742	10,634	6,854	13,332	10,620	6,548	13,407	10,545	6,546

B: Additional Regression Output

Table B1: DD Regression of Score on Percent of District ECD (2023 Excluded)

	Dependent variable:					
	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)
2022	-0.050^{***}	0.013^{***}	-0.228^{***}	-0.090^{***}	-0.125^{***}	-0.022^{***}
	(0.007)	(0.005)	(0.007)	(0.005)	(0.009)	(0.007)
2022 × % ECD	$\mathbf{-0.155}^{***}$	$\mathbf{-0.101}^{***}$			$\mathbf{-0.158}^{***}$	$\mathbf{-0.102}^{***}$
	(0.007)	(0.006)			(0.009)	(0.007)
2022 × In Person			$\mathbf{0.088}^{***}$	$\mathbf{0.044}^{***}$	0.048^{***}	0.024^{***}
			(0.005)	(0.004)	(0.011)	(0.009)
2022 × % ECD × In Person					0.054^{***}	0.022
					(0.019)	(0.015)
Observations	8,998	8,998	8,998	8,998	8,998	8,998
R^2	0.594	0.515	0.596	0.507	0.611	0.523
Adjusted R^2	0.183	0.023	0.187	0.008	0.216	0.039
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Note:						*p<0.1; **p<0.05; ***p<0.01

Table B2: DD Regression of Score on Percent of District Black and Hispanic (2023 Excluded)

	Dependent variable:							
	Math	RLA	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2022	-0.095^{***}	-0.023^{***}	-0.093^{***}	-0.030^{***}	-0.160^{***}	-0.054^{***}	-0.176^{***}	-0.074^{***}
	(0.006)	(0.004)	(0.006)	(0.004)	(0.008)	(0.006)	(0.008)	(0.006)
2022 × % Black	$\mathbf{-0.223}^{***}$	-0.115^{***}			$\mathbf{-0.182}^{***}$	-0.090^{***}		
	(0.010)	(0.007)			(0.012)	(0.009)		
2022 × % Hispanic			$\mathbf{-0.146}^{***}$	$\mathbf{-0.053}^{***}$			$\mathbf{-0.130}^{***}$	$\mathbf{-0.064}^{***}$
			(0.010)	(0.007)			(0.012)	(0.009)
2022 × In Person					$\mathbf{0.068}^{***}$	$\mathbf{0.035}^{***}$	$\mathbf{0.072}^{***}$	0.029^{***}
					(0.006)	(0.005)	(0.006)	(0.005)
2022 × % Black × In Person					-0.041^{*}	-0.035^{*}		
					(0.023)	(0.018)		
2022 × % Hispanic × In Person							0.024	0.063^{***}
							(0.020)	(0.015)
Observations	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998
R^2	0.602	0.512	0.590	0.502	0.611	0.517	0.604	0.511
Adjusted R^2	0.199	0.017	0.175	−0.004	0.217	0.027	0.203	0.014
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:								*p<0.1; **p<0.05; ***p<0.01

Table B3: Regression of Scores on Socioeconomic Status (Excluding 2023)

	Dependent variable:					
	Math	RLA	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)	(5)	(6)
2022	-0.133^{***}	-0.120^{***}	-0.162^{***}	-0.135^{***}	-0.163^{***}	-0.142^{***}
	(0.030)	(0.027)	(0.030)	(0.028)	(0.029)	(0.027)
ECD	-0.594^{***}	-0.596^{***}	-0.610^{***}	-0.601^{***}	-0.578^{***}	-0.577^{***}
	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.006)
2022 × ECD	-0.014^{**}	-0.010^{*}	-0.009	-0.008	-0.009	-0.006
	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)	(0.008)
2022 × In Person			$\mathbf{0.083}^{***}$	0.042^{***}	$\mathbf{0.081}^{***}$	0.045^{***}
			(0.014)	(0.013)	(0.014)	(0.013)
ECD × In Person			0.049^{***}	0.015	0.010	-0.014
			(0.012)	(0.011)	(0.012)	(0.011)
2022 × COVID					0.004	-0.008
					(0.008)	(0.007)
ECD × COVID					0.086^{***}	0.068^{***}
					(0.007)	(0.006)
2022 × ECD × In Person			-0.010	-0.002	-0.009	-0.005
			(0.018)	(0.016)	(0.018)	(0.017)
2022 × ECD × COVID					-0.005	-0.002
					(0.010)	(0.009)
2022 × In Person × COVID					-0.003	0.009
					(0.014)	(0.013)
ECD × In Person × COVID					-0.038^{***}	-0.031^{**}
					(0.013)	(0.012)
2022 × ECD × In Person × COVID					0.006	0.008
					(0.019)	(0.018)
Observations	8,972	8,972	8,972	8,972	8,972	8,972
R^2	0.856	0.873	0.859	0.873	0.859	0.872
Adjusted R^2	0.807	0.830	0.811	0.830	0.811	0.829
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Note:						*p<0.1; **p<0.05; ***p<0.01

Table B4: DDD Regression for Interaction of ECD and Percent of District ECD (Excluding 2023)

	Dependent variable:	
	Math	RLA
	(1)	(2)
2022	-0.098^{***}	-0.079^{***}
	(0.030)	(0.028)
ECD	-0.777^{***}	-0.662^{***}
	(0.011)	(0.010)
2022 × ECD	0.040^{**}	0.009
	(0.017)	(0.016)
2022 × % District ECD	-0.114^{***}	$-\mathbf{0.116}^{***}$
	(0.022)	(0.021)
ECD × % District ECD	0.338^{***}	0.113^{***}
	(0.020)	(0.019)
2022 × ECD × % District ECD	-0.059^{**}	-0.001
	(0.030)	(0.029)
Observations	8,972	8,972
R^2	0.867	0.876
Adjusted R^2	0.822	0.834
District Fixed Effects	Yes	Yes
State-Year Dummies	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table B5: SES Regression Including Pre-COVID trends

	Dependent variable:	
	Math	RLA
	(1)	(2)
2022	−0.165***	−0.142***
	(0.029)	(0.027)
ECD	−0.597***	−0.600***
	(0.006)	(0.006)
Pre-Trend	1.621***	1.296***
	(0.146)	(0.140)
2022 × ECD	−0.010	−0.009
	(0.008)	(0.008)
2022 × In Person	0.085***	0.043***
	(0.014)	(0.013)
ECD × In Person	0.046***	0.033***
	(0.012)	(0.012)
2022 × Pre-Trend	−0.153	−0.118
	(0.113)	(0.095)
ECD × Pre-Trend	−0.087	−0.320***
	(0.109)	(0.095)
In Person × Pre Trend	0.113	0.670**
	(0.332)	(0.339)
2022 × ECD × In Person	−0.010	−0.008
	(0.018)	(0.017)
2022 × ECD × Pre-Trend	−0.001	0.009
	(0.154)	(0.135)
2022 × In-Person × Pre-Trend	−0.024	−0.029
	(0.224)	(0.225)
ECD × In-Person × Pre-Trend	0.222	0.786***
	(0.220)	(0.225)
2022 × ECD × In-Person × Pre-Trend	−0.106	−0.258
	(0.310)	(0.320)
Observations	8,972	8,972
R^2	0.866	0.878
Adjusted R^2	0.820	0.836
District Fixed Effects	Yes	Yes
State-Year Dummies	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table B6: Regression of Scores on Race (2023 Included)

	Dependent variable:			
	Math	RLA	Math	RLA
	(1)	(2)	(3)	(4)
2022	-0.100^{***}	-0.033	-0.104^{***}	-0.034
	(0.030)	(0.031)	(0.031)	(0.033)
2023	-0.078^{***}	0.099^{***}	-0.083^{***}	0.097^{***}
	(0.030)	(0.031)	(0.031)	(0.033)
Black	-0.780^{***}	-0.720^{***}	-0.808^{***}	-0.744^{***}
	(0.016)	(0.017)	(0.019)	(0.020)
Hispanic	-0.522^{***}	-0.565^{***}	-0.555^{***}	-0.601^{***}
	(0.017)	(0.018)	(0.021)	(0.022)
2022 × Black	-0.028	-0.018	-0.020	-0.013
	(0.024)	(0.025)	(0.029)	(0.030)
2023 × Black	-0.028	-0.001	-0.019	0.002
	(0.024)	(0.025)	(0.029)	(0.030)
2022 × Hispanic	-0.054^{**}	-0.041	-0.057^{*}	-0.043
	(0.026)	(0.027)	(0.030)	(0.031)
2023 × Hispanic	-0.069^{***}	-0.052^{*}	-0.068^{**}	-0.052^{*}
	(0.026)	(0.027)	(0.030)	(0.031)
2022 × In Person			0.047	0.011
			(0.070)	(0.074)
2023 × In Person			0.053	0.018
			(0.070)	(0.074)
Black × In Person			0.171^{**}	0.139^{*}
			(0.075)	(0.079)
Hispanic × In Person			0.222^{**}	0.257^{***}
			(0.090)	(0.095)
2022 × Black × In Person			-0.050	-0.037
			(0.110)	(0.116)
2023 × Black × In Person			-0.053	-0.019
			(0.110)	(0.116)
2022 × Hispanic × In Person			0.039	0.017
			(0.132)	(0.139)
2023 × Hispanic × In Person			0.001	-0.001
			(0.131)	(0.139)
Observations	1,179	1,179	1,179	1,179
R^2	0.856	0.825	0.857	0.826
Adjusted R^2	0.834	0.798	0.834	0.798
District Fixed Effects	Yes	Yes	Yes	Yes
State-Year Dummies	Yes	Yes	Yes	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

Table B7: DDD Regression for Interaction of Race and Percent of District ECD

	Dependent variable:	
	Math	RLA
	(1)	(2)
2022	−0.056	0.017
	(0.050)	(0.054)
2023	−0.034	0.132**
	(0.050)	(0.054)
Black	−0.880***	−0.712***
	(0.051)	(0.054)
Hispanic	−0.788***	−0.783***
	(0.051)	(0.055)
2022 × Black	−0.061	−0.026
	(0.077)	(0.081)
2023 × Black	−0.042	0.015
	(0.077)	(0.081)
2022 × Hispanic	−0.050	−0.027
	(0.075)	(0.080)
2023 × Hispanic	−0.075	−0.028
	(0.075)	(0.080)
2022 × % ECD	−0.092	−0.108
	(0.089)	(0.094)
2023 × % ECD	−0.092	−0.072
	(0.089)	(0.094)
Black × % ECD	0.206**	0.003
	(0.088)	(0.092)
Hispanic × % ECD	0.494***	0.389***
	(0.090)	(0.096)
2022 × Black × % ECD	0.069	0.027
	(0.131)	(0.137)
2023 × Black × % ECD	0.036	−0.020
	(0.132)	(0.138)
2022 × Hispanic × % ECD	0.006	−0.009
	(0.132)	(0.140)
2023 × Hispanic × % ECD	0.024	−0.030
	(0.132)	(0.140)
Observations	1,179	1,179
R^2	0.862	0.822
Adjusted R^2	0.840	0.793
District Fixed Effects	Yes	Yes
State-Year Dummies	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table B8: Race Regression Including Pre-COVID trends

	Dependent variable:	
	Math	RLA
	(1)	(2)
year2022	−0.113***	−0.050
	(0.030)	(0.033)
Black	−0.760***	−0.705***
	(0.017)	(0.018)
Hispanic	−0.511***	−0.539***
	(0.017)	(0.019)
Pre-Trend	3.896***	5.562***
	(0.468)	(0.526)
2022 × Black	−0.013	−0.009
	(0.024)	(0.025)
2022 × Hispanic	−0.043*	−0.041
	(0.024)	(0.027)
2022 × In Person	0.049	0.018
	(0.041)	(0.042)
Black × In Person	0.038	0.057
	(0.042)	(0.046)
Hispanic × In Person	0.010	0.020
	(0.038)	(0.043)
2022 × Pre-Trend	−0.078	−0.166
	(0.323)	(0.269)
Black × Pre-Trend	0.099	−0.649**
	(0.339)	(0.302)
Hispanic × Pre-Trend	0.203	−0.214
	(0.358)	(0.315)
In Person × Pre-Trend	−4.561***	−7.100***
	(1.093)	(1.269)
2022 × Black × In Person	−0.046	−0.027
	(0.060)	(0.065)
2022 × Hispanic × In Person	−0.008	−0.012
	(0.055)	(0.061)
2022 × Black × Pre-Trend	−0.341	−0.145
	(0.492)	(0.442)
2022 × Hispanic × Pre-Trend	−0.623	−0.215
	(0.516)	(0.452)
2022 × In Person × Pre-Trend	0.409	−0.164
	(0.819)	(0.834)
Black × In Person × Pre-Trend	1.736*	2.068**
	(0.968)	(1.019)
Hispanic × In Person × Pre-Trend	2.088**	1.824**
	(0.924)	(0.907)
2022 × Black × In Person × Pre-Trend	0.255	0.149
	(1.402)	(1.490)
2022 × Hispanic × In Person × Pre-Trend	1.132	0.099
	(1.314)	(1.286)
Observations	1,488	1,488
R^2	0.870	0.847
Adjusted R^2	0.839	0.811
District Fixed Effects	Yes	Yes
State-Year Dummies	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

5.1 C: Figures

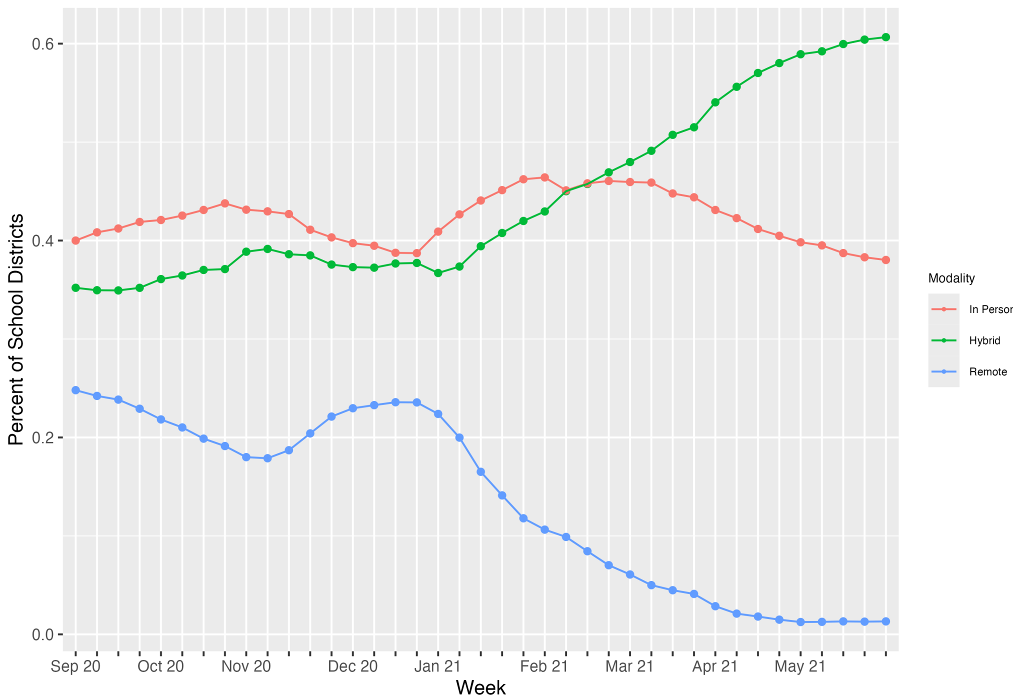


Figure C1: Modality of School Districts Over the 2020–2021 School Year

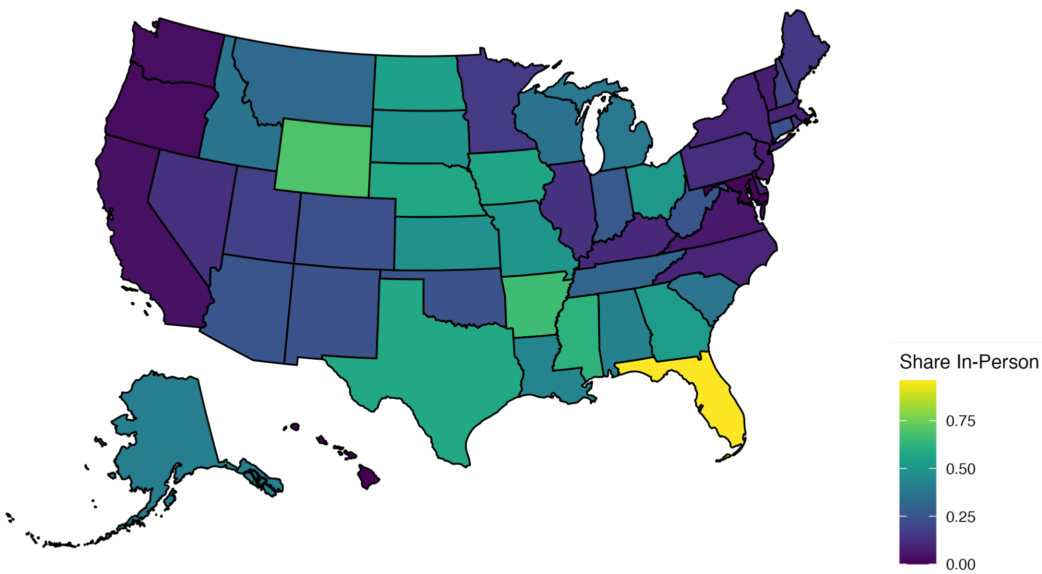


Figure C2: Percent of Instruction That Was Fully In-Person During the 2020–21 School Year by State

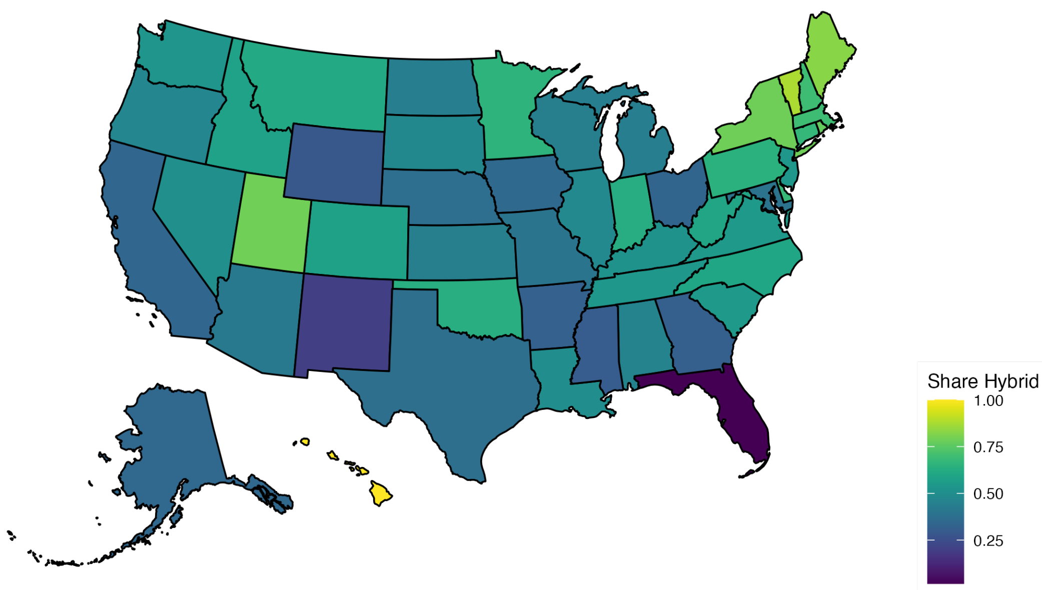


Figure C3: Percent of Instruction That Was Hybrid During the 2020–21 School Year by State

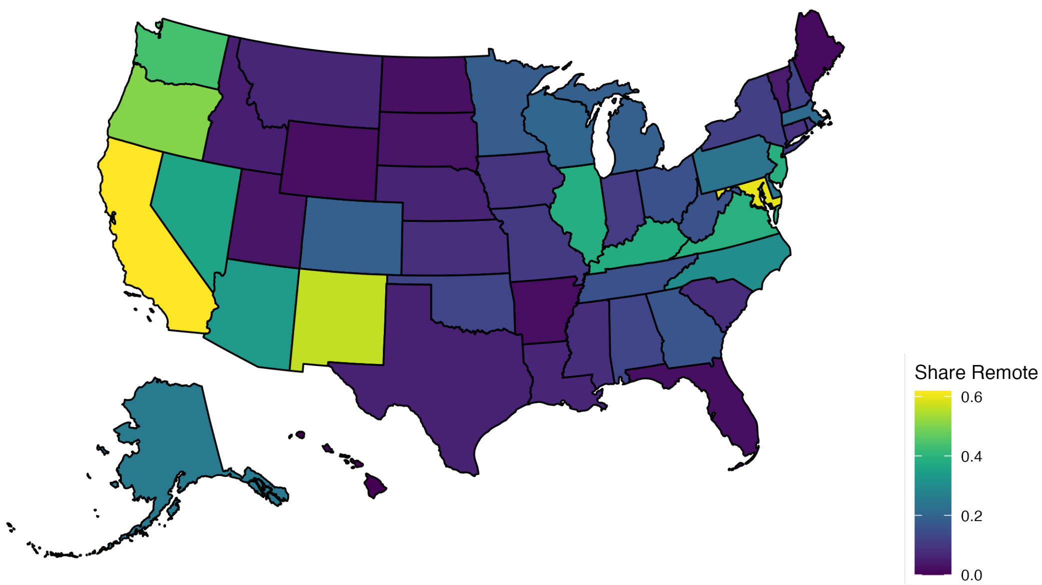


Figure C4: Percent of Instruction That Was Fully Remote During the 2020–21 School Year by State

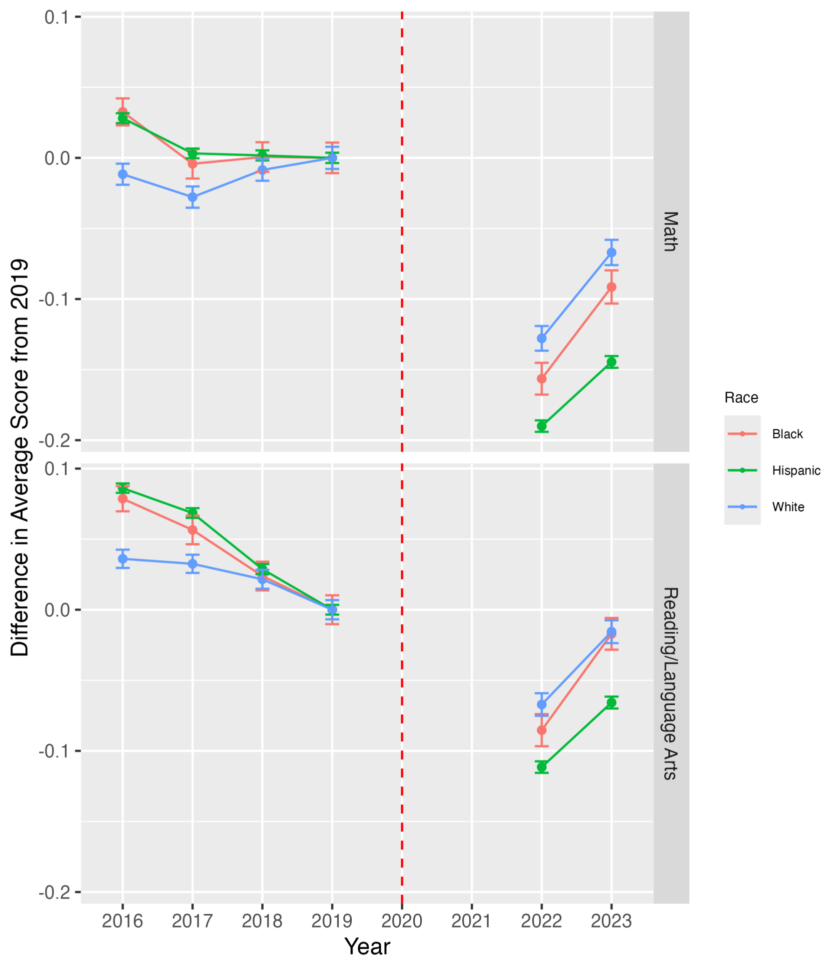


Figure C5: Average Scores By Subject and Race – Data Set F

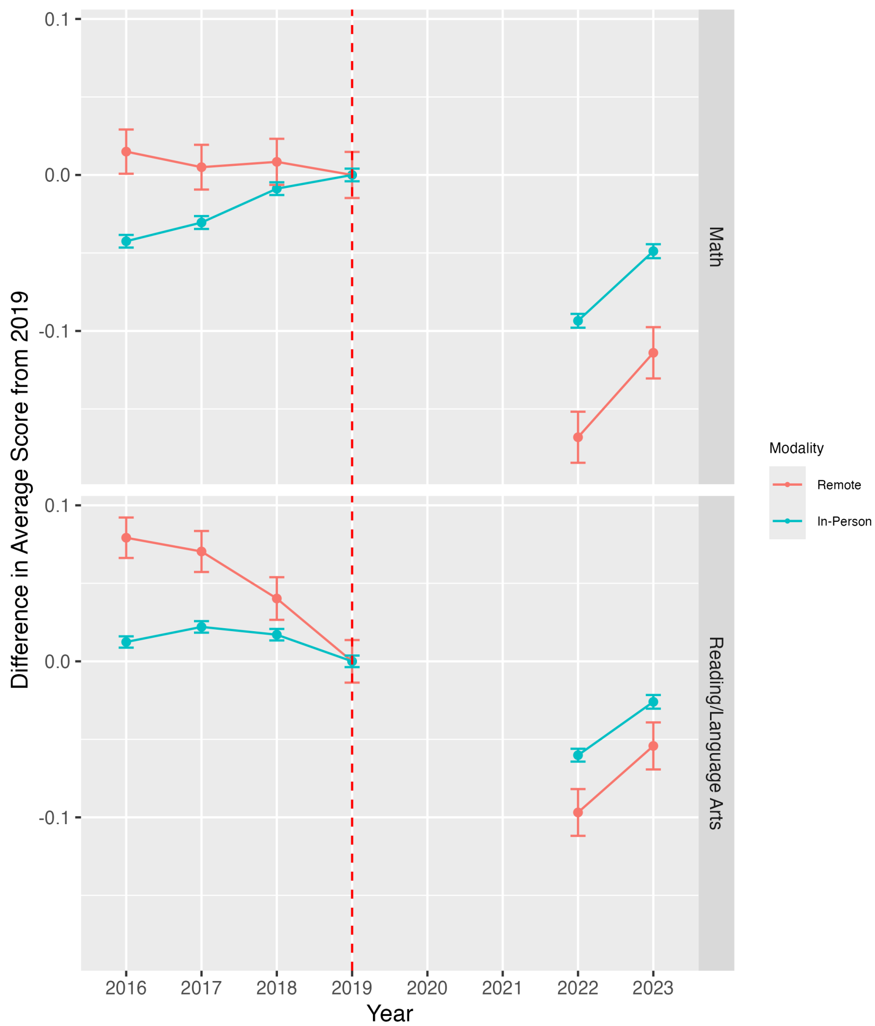


Figure C6: Average Scores by Modality – Data Set B

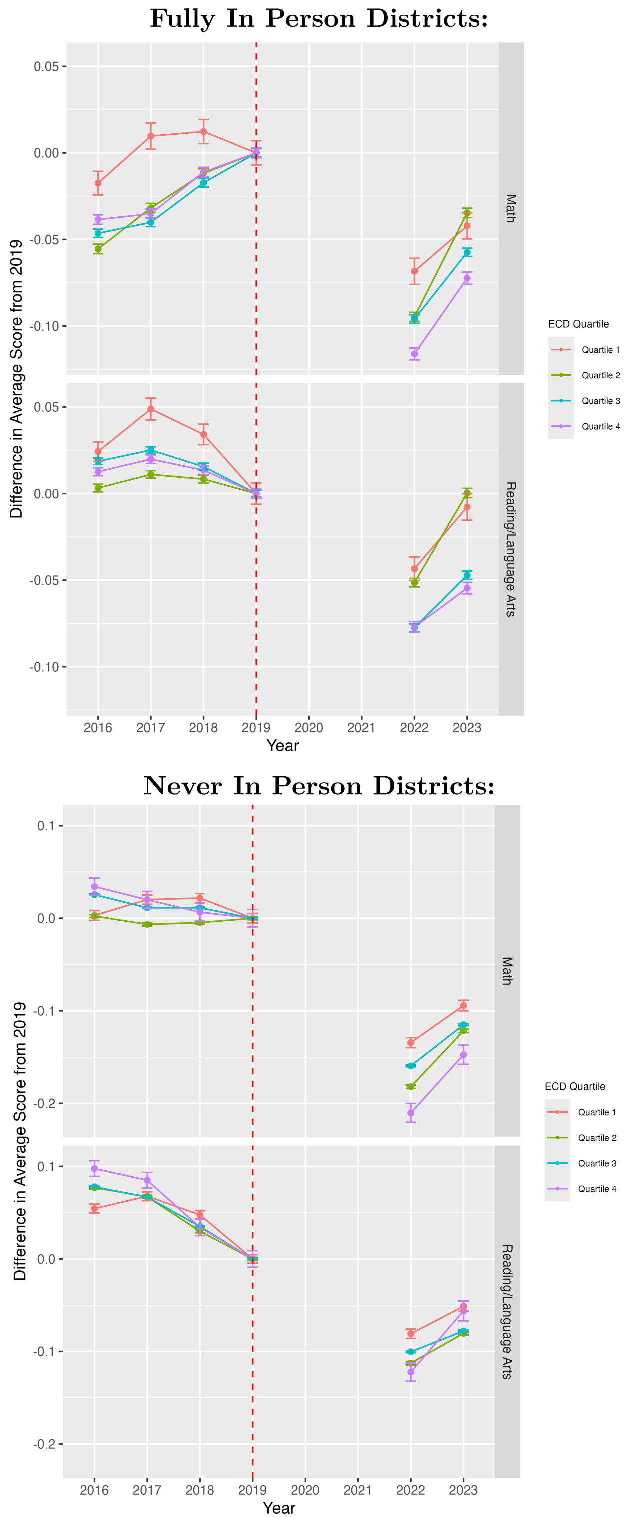


Figure C7: Average Scores by Modality and Percent of District Economically Disadvantaged – Data Set B

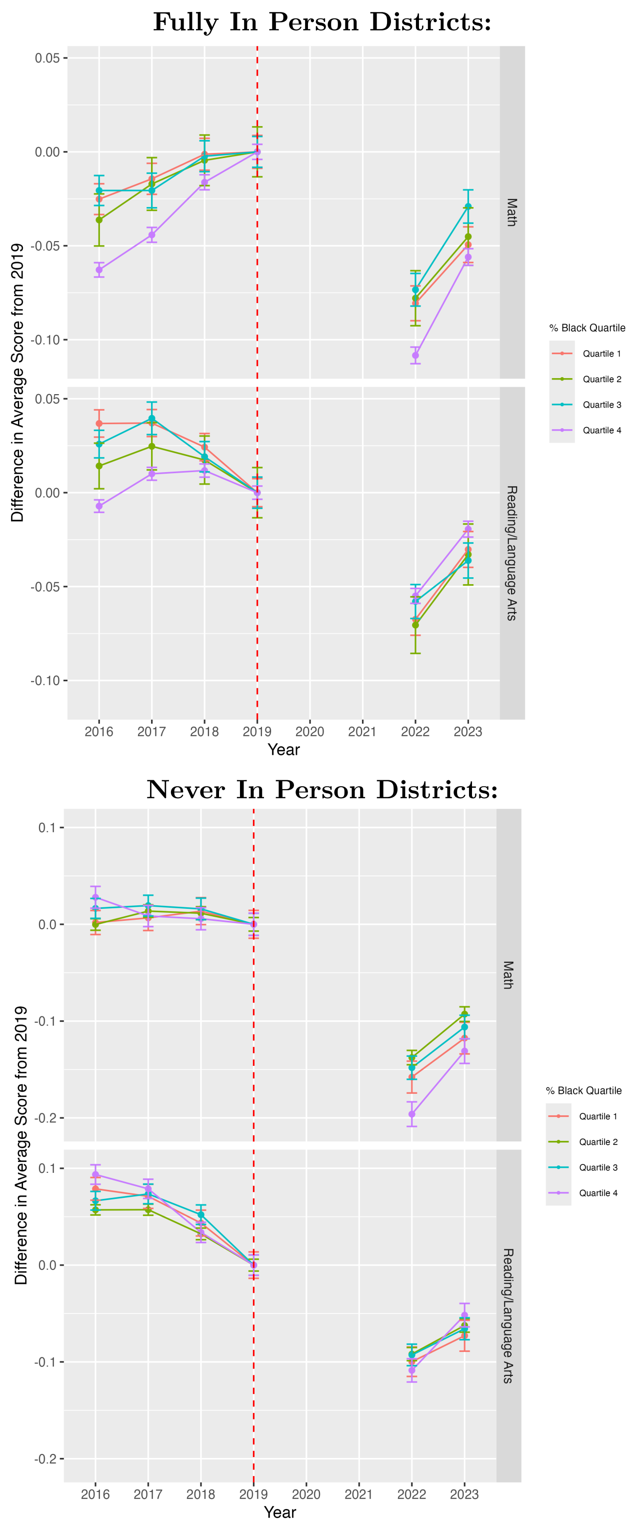
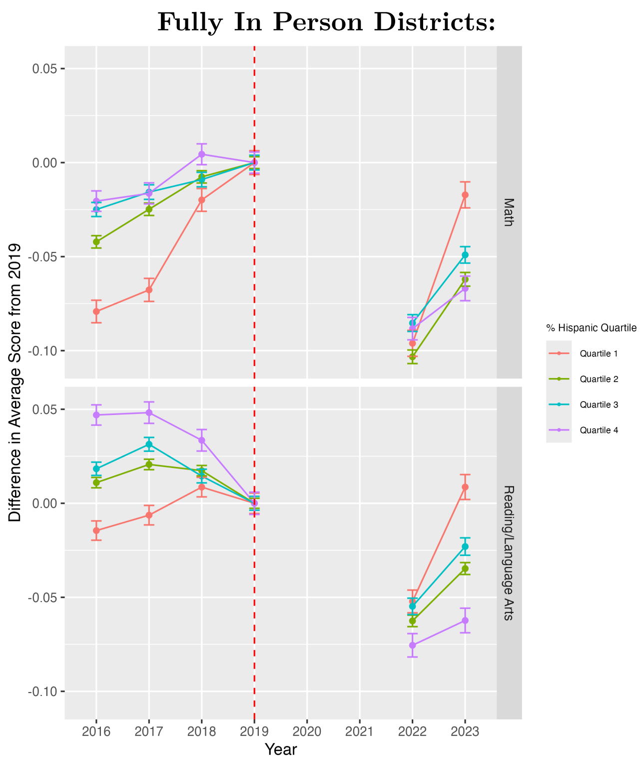


Figure C8: Average Scores by Modality and Percent of District Black – Data Set B



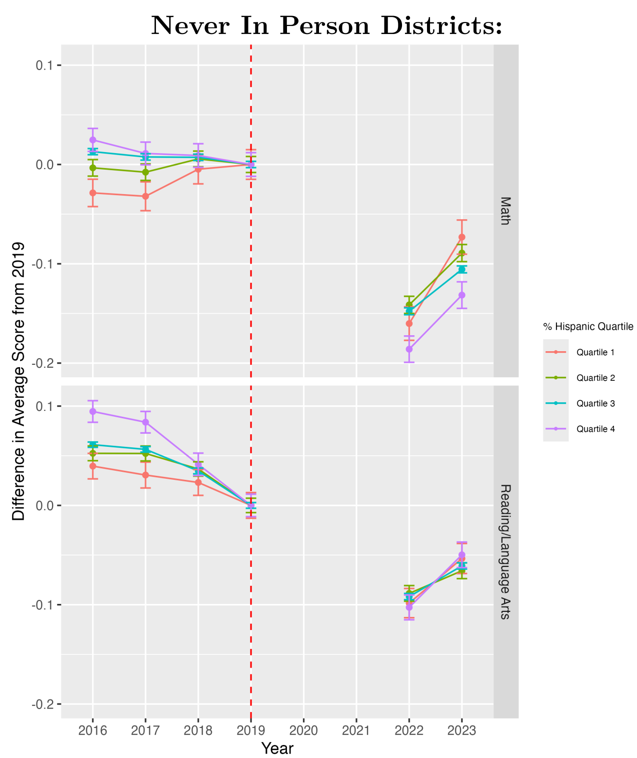


Figure C9: Average Scores by Modality and Percent of District Hispanic – Data Set B