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School District and Community Factors Associated With Learning Loss During the COVID-19 Pandemic

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Abstract

We analyze data from approximately 7,800 school districts to describe variation in pandemic-related learning losses among communities and student subgroups. We attempt to understand mechanisms that led to learning losses, as well as explore how historical data from those districts can inform our expectations for how quickly districts will rebound from such losses. We show that learning losses during the pandemic were large and highly variable among communities. Similar to previous research, we find that losses were larger in lower-income and minority districts and in districts which remained remote or hybrid for longer periods during the 2020-21 school year. Among districts, the math learning loss per week of remote/hybrid instruction was larger in high-minority and high-poverty districts. Within districts, however, White students and non-economically disadvantaged students lost about the same amount of ground as Black, Hispanic and economically disadvantaged students. This suggests that the mechanisms driving losses operated at the district or community level, rather than household level. Several community-level characteristics were related to learning losses: broadband access, disruptions to social and economic activity, and trust in government institutions. However, no individual predictor provided strong explanatory power. Relative to historical years, losses during the pandemic were substantial, and an exploratory analysis of historical shocks to achievement suggests that the effects of the pandemic are likely to persist without continued concerted investments in student learning.

Introduction

Between 2019 and 2022, mean achievement on the National Assessment of Educational Progress (NAEP)[1] fell by eight points in eighth grade math (roughly three-quarters of a grade level[2]) and by three points in eighth grade reading (roughly one-quarter of a grade level). However, the impacts were uneven. For example, in eighth grade math, the differences in average NAEP scores were small or non-significant in some states, while 11-12 points in others (equivalent to a full grade level). Such variation in these impacts should not be surprising. The pandemic affected nearly every aspect of students' lives— their school experiences, their social networks, their parents' jobs and income, their mental health, among others. But the contributions of these factors to student's learning during the pandemic are still not well understood.

Our goals in this paper are three-fold. First, we describe patterns of declines in test scores between 2019 and 2022, or "learning losses," among school districts. We use the term "learning loss" to indicate that students lost opportunities to learn during the pandemic and thus realized less learning than prior cohorts at the same grade levels.[3] We have assembled a unique data set of district-level achievement in 7,800 school districts across 41 states from 2009 to 2022 that enables us to explore variation in changes in achievement both between districts and within them, among student subgroups. This analysis sheds light on both the extent of variation among districts in learning losses, as well as whether losses are shaped by district and community factors.

Second, we explore a larger set of potential district and community-level mechanisms through which the pandemic may have affected achievement than earlier research has. We draw on various data sources, including data on school closures and instructional mode; district staffing, racial and economic composition, and enrollment; household broadband access; county-level COVID death rates, survey data on pandemic behaviors; voting patterns; and other measures of local economic and social behavior during the pandemic, such as expenditures on restaurants and entertainment. Using these data, we construct measures of the economic, social, health, and schooling context of students in each school district in our sample. We present descriptive analyses of the associations between these measures and learning losses from 2019-2022. To best identify these associations, we make three empirical contributions. We account for district characteristics that relate to trends in general, including before the pandemic, by using the differential change in achievement between 2019-22 relative to the three-year change immediately before the pandemic (2016-19) as our dependent variable. We further identify the relationships of key predictors with the trends using only within-state variation by including state fixed effects and differencing each district characteristic or community-level factor from the relevant state mean in our analyses. States had widely varying policy responses to COVID and, thus, state characteristics may be correlated with some of the mechanisms explored. Additionally, because our data are cross-sectional (not longitudinal), the shifting composition of students in districts is a concern. Public school

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[1] NAEP results are retrievable from: https://www.nationsreportcard.gov.

[2] The number of points roughly corresponding to a grade level is approximated by taking the subject-specific difference in the average 8th grade and 4th grade scores in 2019 and dividing by four.

[3] As an example, the decline in the average 8th grade NAEP scores indicates that 8th graders in 2022 had developed fewer math and reading skills than 8th graders in 2019 had at the same point in the school year. These students had learned less than prior cohorts at the same grade level. Importantly, it does not mean that the average student lost math or reading skills they had acquired prior to the pandemic.

enrollment declined following the pandemic as many students withdrew from public schools to enroll in private, on-line, or home-school alternatives or simply disappeared from school rolls (Dee, 2023). We adjust for these changes by including changes in the overall enrollment, racial composition, and economic composition in districts as covariates in our models.

Third, we contextualize the pandemic losses, and subsequent recovery, using historical data from 2009 to 2019. We identify the longer-term achievement patterns of district-cohorts who experienced sizeable shocks (increases or decreases) to their test scores in a given year. This analysis provides insight into the magnitude of the COVID learning losses relative to losses in prior years and into the extent to which schools and students can be expected to rebound from disruptions.

We show the learning losses during the pandemic were large and highly variable among communities. As others have reported, we find that the losses were larger in lower-income and minority districts and in districts which remained remote or hybrid for longer periods (Goldhaber et al., 2022a; Jack et al., 2022). In math, the loss per week of remote/hybrid instruction was larger in high-minority and low-income districts. However, within the average district, White students and non-economically disadvantaged students lost about the same amount of ground as Black, Hispanic and economically disadvantaged students. This suggests that the mechanisms, whatever they were, operated at the district or community level, affecting those student subgroups similarly within districts. Third, we find that a number of additional community-level characteristics were related to learning losses: broadband access, COVID-19 related disruptions to normal social and economic activity, and trust in government institutions (as measured by voter participation and Census response rates). Finally, we show that in the decade before the pandemic, shocks to achievement (large increases and decreases) for specific age cohorts have largely persisted, even 4-5 years later. Historically, it has been difficult for districts to adjust the pace of learning following a disruption. Unless districts are more successful in accelerating learning this time, the losses could persist.

Literature Review

Since the beginning of the pandemic, several reports have documented learning losses in U.S. schools. Much of that research has relied on student-level data from subsets of districts using specific assessments—not a nationally representative sample (Amplify, 2021; Bielinski et al., 2021; Domingue et al., 2022; Goldhaber et al., 2022a; Goldhaber et al., 2022b; Kuhfeld et al., 2022; Lewis et al., 2021; Locke et al., 2022). Other studies used data from specific states (Jack et al., 2022; Kogan & Lavertu, 2021; Kozakowski et al., 2021; Pier et al., 2021). Such research has typically reported larger losses in math than in reading (Lewis & Kuhfeld, 2022), and larger losses in high poverty schools than in low poverty schools (Kuhfeld et al, 2022). These patterns are not unique to the U.S. In a meta-analysis of 42 studies of learning losses across 15 countries, Betthäuser et al. (2023) report a consistent pattern of widening achievement gaps by income and socioeconomic status, with larger losses among more disadvantaged students.

There are many possible reasons that students in some districts may have been more severely impacted during the pandemic—both due to school-related and non-school factors. In prior research, the extent of time in remote instruction has been identified as a particularly crucial factor. Using district-level data, Jack et al. (2022) reported smaller declines in proficiency rates per week of in-person instruction in school districts with more Black students. Goldhaber et al. (2022a) found that losses were larger for students in higher poverty schools, and that higher-poverty schools remained in remote instruction for longer periods during the 2020-21 school year. However, in districts that returned to in-person instruction quickly (spending less than 4 weeks remote during the 2020-21 school year), Goldhaber et al. (2022a) report that high and low-poverty schools lost about the same amount of ground. In addition, Goldhaber et al. (2022a) found that the higher incidence of remote schooling accounted for one-third of the widening of the gap in scores on the NWEA MAP assessment between high and low-poverty schools, with the greater impact per week of remote instruction accounting for most of the remaining two-thirds of the widening gap. Other studies have also reported greater incidence of remote instruction for Black and Hispanic students (Parolin & Lee, 2021; Camp & Zamarro, 2022; Grossmann et al., 2021; Oster et al., 2021).

Unfortunately, neither Goldhaber et al. (2022a) nor Jack et al. (2022) provide insight into the mechanisms by which higher poverty schools lost more ground per week of remote instruction. For instance, it could be that their schools were less prepared for or had fewer resources to facilitate the shift to remote instruction, that their students had more limited access to computers or broadband access at home, or that parents may have had less time to devote to monitor students' engagement with online instruction. It could also be that community-level factors—such as COVID death rates or the magnitude of employment losses—were either correlated with school closures or mediated the effect of school closures on poor or disadvantaged students. There are also important racial contexts to consider. For instance, for all age groups, the Center for Disease Control and Prevention reported higher death rates for Black and Hispanic persons in the U.S. than for non-Hispanic Whites and Asians.[4] Moreover, the Bureau of Labor Statistics reported unemployment rates during 2021 of 8.6 and 6.8 percent for Black and Hispanic adults in the U.S., as compared to 4.7 percent for Whites and 5.0 percent for Asians.[5] In addition, while rates of depression and anxiety spiked for all racial/ethnic groups during the pandemic, Thormeer et al. (2023) report larger increases for Black and Hispanic adults. Each of these factors—death rates, unemployment, depression and anxiety—may have affected students' own mental health and ability to focus on schooling and may have affected parents' ability to help their children with schooling. The racial disparities in these factors might produce racial disparities in the impact of the pandemic on student learning. In this analysis, we extend the prior literature by explicitly examining the association of such social, economic, and health factors with patterns of learning loss.

Factors Hypothesized to Affect Learning Loss

In this paper we explore how learning loss varied by district characteristics, instructional modality and eight additional factors that we hypothesize could have contributed to the pandemic-related decline in test scores. Some of these factors capture differences in the pre-existing level of resources available to respond to the pandemic, while others capture differences across school districts in the impact of the pandemic. More details on each of the factors can be found in the Measures section below and in Appendix Tables A3 and A4.

[4] https://www.cdc.gov/nchs/nvss/vsrr/covid19/health_disparities.htm#RaceHispanicOrigin
[5] https://www.bls.gov/opub/reports/race-and-ethnicity/2021/home.htm

District demographic characteristics. Given the literature referenced above indicating different experiences across racial and ethnic groups and across groups with different economic situations we explore both district poverty and racial composition to better understand how learning loss varied among places.

Instructional modality. Virtually every school in the country rapidly switched from in-person to remote instruction in the spring of 2020. And most schools were remote for a period of a week or more between August 2020 and May 2021,[6] though the share of time students were fully remote or hybrid (a combination of in-person and remote instruction) varied. Prior evidence, discussed above, suggests that districts that spent more time in remote instruction during 2020-21 experienced greater losses.

Home computer and internet access. Increasingly, students require access to a computer and to reliable, high-speed internet access to be able to complete their schoolwork. This became of dire importance during school building closures; without such access, students had difficulty participating in remote classes.

School resources. School district staff faced unprecedented challenges in responding to the pandemic, including pivoting to remote instruction in a matter of weeks with little warning in March 2020, accommodating high rates of staff absences due to illness, and modifying classrooms and instruction to minimize risk of transmission and facilitate onsite instruction. School districts with more staff and other resources may have had greater capacity to respond to these challenges.

Local social capital. Both schools and households relied on broader community support during the pandemic, from volunteers in the schools to learning communities that formed to support remote instruction. Communities with more social capital, greater civic and volunteer participation, and more connectedness among residents may have been better able to maintain social connections among residents and to better support schools and households. Some research has shown that communities with stronger social networks and connections are less negatively impacted by natural disasters (Klinenberg, 2002; Partelow, 2021).

Trust in institutions. Residents in communities where individuals actively participate in civic activities (e.g., voting and responding to the census), and express confidence that institutions, including public schools, act in a beneficial manner may have been more willing to cooperate with their local schools and reduce disruptions to student learning.

Pandemic employment. Unemployment rates spiked during the pandemic, as many workers lost their jobs. These job losses may have affected children's learning, both because of their economic impact on families and because of the parental and child anxiety and stress that results from parental unemployment (Stevens & Schaller, 2011; Rege et al., 2011; Ananat et al., 2011). As a result, communities with more unemployment may have experienced larger losses. On the other hand, having a non-working adult in the household may have been helpful to students in the transition to remote learning, reducing losses. The expected net effects, therefore, are unclear.

[6] Most schools reopened for the 2021-22 school year, so the instructional modality in the 2020-21 school year captures the majority of the variability in remote/hybrid learning across the two years.

Deaths from COVID-19. During the pandemic many households had family members, relatives, and friends who were infected with COVID-19, many of whom became seriously ill or died. Student learning is directly affected by the trauma and fear associated with the serious illness or death of a friend or family member. School districts with greater prevalence of serious illness or death due to COVID-19 may have had more students and school staff affected by this trauma and therefore had greater learning loss.

COVID-19 disruptions to normal life. The pandemic caused general disruptions to day-to-day life. At some points in time and in some areas, children were unable to socialize with their friends in person or to participate in extracurricular activities; many restaurants, retail stores, movie theaters, and churches were closed. The extent of such closures and restrictions varied markedly among communities in the U.S. In areas where social activities were curtailed and businesses and institutions were shut down longer, students and school staff may have been more affected—more anxious, more depressed. As a result, in school districts where students and teachers were more able to continue with normal life during the pandemic, student learning losses may have been smaller. Additionally, communities that took more precautions to avoid COVID-19 infection, including vaccinating and masking, may have been able to engage in these activities more and had fewer illness-related disruptions.

Anxiety and depression. The pandemic has had lasting impacts on mental health of both children and adults (Ettman et al., 2023). Many students had difficulty learning during the pandemic due to mental health challenges that affected them or adults in their household. School districts with greater prevalence of student mental health issues, both before and during the pandemic, may have found it harder to maintain learning during the pandemic. And among adults, including teachers, COVID led to increased anxiety, depression, and stress among adults (Kush et al., 2022). These effects were most pronounced for those who lost their jobs (Gassman-Pines et al., 2020). This may have affected teachers' ability to teach effectively and may have affected parents' ability to support their children's learning (whether remote or at home).

Data

In this section, we describe the source data and measures used in this study.

Achievement Data and Measures

The achievement data come from a restricted-use version of Stanford Education Data Archive 2022 Version 2.0 (SEDA; Reardon et al., 2023).[7,8] SEDA provides test score estimates for schools and districts

[7] The data used in this study are disaggregated by administrative school district, subject, grade, and year. These data are not provided publicly in SEDA or on the Educational Opportunity Project website: https://www.edopportunity.org. The public 2009-2018 SEDA 4.1 data do not include test score estimates for administrative school districts. The 2019 and 2022 data provided in SEDA2022 include estimates for administrative school districts; however, these are pooled over grades within subject-years. These data are an extension of those we used in a prior report (Fahle et al., 2022).
[8] Test score estimates in SEDA for years 2009-2019 are based on data from ED*Facts* and provided by the National Center for Education Statistics. Test score data in 2022 are based on state-reported accountability data. Both sources of data contain counts of students in each district-grade-year-subject-subgroup scoring in each of multiple ordered proficiency categories (often labeled something like "below basic", "basic", "proficient", and "advanced"). SEDA uses these raw counts to estimate the mean test score in each district-grade-year-subject-subgroup using a

from 2009 through 2022 in math and reading language arts (we refer to this as reading, throughout) for grades 3 to 8 for all students and for racial and economic subgroups. The test score estimates are constructed from state accountability test data and linked to the NAEP, such that they are comparable across states and time.

For our primary analyses of learning losses, we use estimates of 3-8th grade average math and reading test scores in 2016, 2019, and 2022, along with their standard errors, for administrative school districts[9] in math and reading for all, White, Black, Hispanic, economically disadvantaged, and non-disadvantaged students.[10] The estimates are reported in the grade-year scale; in this scale one unit is approximately one grade level.[11] For additional details on the SEDA2022 construction methodology, see the technical documentation (Fahle et al., 2023).[12] In total, we have achievement data for all students in 41 states, for racial/economic subgroups in 30 states, and for economic disadvantage subgroups in 27 states.

We estimate the model in equation (1), separately by subgroup and subject, using district-grade-year-subject-subgroup data from 2016, 2019, and 2022. The model pools data across grades to provide two estimates of the district-subgroup-subject learning loss: 1) the simple difference in average scores from 2019 to 2022; and 2) a difference-in-difference estimate of the pandemic-induced change in average scores, computed by subtracting the 2016 to 2019 change in scores from the 2019 to 2022 change in scores. The difference-in-difference estimate describes the deviation of the 2019-2022 change from the prior three-year trend in scores, and so implicitly controls for prior trends in average test scores within a district. We refer to this difference-in-differences estimates as the "differential change."

In model (1), y_{dyg} is the (unobserved) true average test score in grade g and year y in district d, and $\hat{y}_{dyg} = y_{dyg} + e_{dyg}$ is the estimated average test score (estimated from the raw proficiency count data via the HETOP and linking methods described above), where the estimation error e_{dgy} is assumed normally distributed with variance $\hat{v}^2_{dgy}$ (where $\hat{v}_{dgy}$ is the estimated standard error of $\hat{y}_{dgy}$). In addition, $year$ is a linear year term (equal to 2016, 2019, or 2022); $grade$ is a linear grade term (ranging from 3 to 8); and I^{2016} and I^{2022} are dummy variables taking on the value of 1 for year 2016 or 2022, respectively, and 0 otherwise. The parameters $\gamma_{00}, \dots, \gamma_{40}$, the variance σ^2, and the 4×4 variance-covariance matrix $\boldsymbol{\tau}$ are estimated via restricted maximum likelihood using the HLM software.

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heteroskedastic ordered probit (HETOP) model, and then links each state's test scores to the NAEP scale using the methods described in Reardon et al. (2017) and Reardon et al. (2021a).

[9] Administrative school districts operate sets of public and charter schools. The schools operated by each school district are identified using the National Center for Education Statistics (NCES) school and district identifiers. Most commonly, administrative school districts operate local public schools within a given physical boundary. There are also specialized administrative districts, like charter school and virtual school districts, that do not have a physical boundary. For this paper, we only use administrative school districts that have a physical boundary.

[10] States report data by economic disadvantage. We use the term (non-)poor to indicate students identified as (not) economically disadvantaged. In most states, economically disadvantaged is equivalent to eligible for free and reduced-price lunch.

[11] Grade levels are defined using the 2019 national NAEP 4th and 8th grade data. One grade level is approximated as the average number of NAEP points student test scores differ per grade in each subject.

[12] The data used in this study are equivalent to the "long form" estimates described in the documentation.

$$\hat{y}_{dyg} = y_{dyg} + e_{dyg}$$
$$y_{dyg} = \beta_{0d} + \beta_{1d}\left(\frac{year - 2019}{3}\right) + \beta_{2d}(I^{2016}) + \beta_{3d}(grade - 5.5) + \beta_{4d}((grade - 5.5)(I^{2022}) + r_{dyg}$$
$$\beta_{0d} = \gamma_{00} + u_{0d}$$
$$\beta_{1d} = \gamma_{10} + u_{1d}$$
$$\beta_{2d} = \gamma_{20} + u_{2d}$$
$$\beta_{3d} = \gamma_{30} + u_{3d}$$
$$\beta_{4d} = \gamma_{40}$$

$$e_{dgy} \sim N\left[0, \hat{v}^2_{dgy}\right];\ r_{dgy} \sim N[0, \sigma^2];\ [u_{0d}, \dots, u_{3d}] \sim MVN[\mathbf{0}, \boldsymbol{\tau}]. \tag{1}$$

In this model, β_{0d} is the 2019 average grade 5.5 test score for district d, β_{1d} is the 2019-22 simple difference in test scores for district d; β_{2d} is the 2019 difference-in-difference measure of test score change for district d; β_{3d} is the grade slope for district d in 2016 and 2019; and β_{4d} (assumed constant over districts) is the average difference in grade slopes between the early two years and 2022. The estimation produces both "OLS" (unshrunken) estimates of the β's and Empirical Bayes (shrunken) estimates. We use the district-level unshrunken estimates $\hat{\beta}_{1d}$ (the "simple change from 2019-22") and $\hat{\beta}_{2d}$ (the "difference-in-difference change from 2019-22, relative to pre-pandemic") produced by HLM as our outcome measures in subsequent models.[13] We use their standard errors as precision weights in all analyses. We also fit a reparameterized variant of this model to produce unshrunken estimates of the simple change from 2016-19 (which is simply $\hat{\beta}_{1d} - \hat{\beta}_{2d}$ from Model 1) and their standard errors for use in a subset of analyses.

The first six rows in Table 1 show the 2019-22, 2016-19, and differential 2019-22 change relative to pre-pandemic for all students in math and reading; summary statistics for the subgroup samples are shown in Appendix Table A1.[14] In total, we have estimates from 41 states and 7,729 districts for math, and 39 states and 7,510 districts for reading.[15] The average district in our sample experienced a half a grade level (-0.494) change in math achievement between 2019 and 2022. The average losses among districts varied widely across the entire sample (overall SD = 0.371) and within states (within-state SD = 0.300). The differential change in math is also approximately half a grade level (-0.515), with slightly smaller variation within states (SD = 0.262). In reading, the changes in achievement were smaller (-0.309 grade levels) and the differential change is much smaller (-0.102 grade levels). The reason the differential trend in reading

[13] In figures that show estimates of β_{1d} or β_{2d} for individual districts, however, we use the shrunken estimates. Because we fit model 1 separately by subject-subgroup, these estimates are shrunk toward the overall mean.

[14] The mean and standard deviations (SDs) are calculated as $\sqrt{\tau^2}$ from a precision-weighted regression model (fit using the `-metareg-` command in Stata); also known as a meta-analytic regression model, this model estimates the mean and variance of the distribution of true values (as opposed to the mean and variance of the distribution of noisy estimated values). The mean and overall SD are from a null model; the within-state SD is from a precision-weighted regression model that includes state fixed effects.

[15] The difference in the number of usable district-subject estimates in math and reading is driving by the exclusion of Arkansas and West Virginia in reading. The proficiency data provided was not useable for SEDA data construction; see the technical documentation (Fahle et al., 2023) for more details.

was much smaller than the simple trend is because, on average, reading test scores were declining between 2016 and 2019 (a trend that is evident in NAEP reading scores from 2015 to 2019 as well as in the district estimates we use here). Similar to math, the reading estimates vary significantly overall and within states.

For the persistence analysis, we use a data set of estimates of achievement at the district-subject-grade-year level from 2009-19 to measure prior shocks.[16] For the analysis of persistence among cohorts, we require districts to have estimates available for complete cohorts, and for each grade-year cell within a cohort to have at least 100 test-takers.[17] A district-subject must also have at least two complete cohorts to be included in the analysis. The resulting sample includes cohorts from 2,719 districts in math and 3,637 districts in reading.

Covariate Data and Measures

We gathered district and county-level[18] covariate data from a variety of sources:

- The Common Core of Data (CCD), collected by the National Center for Education Statistics (NCES), provides annual information on school characteristics.[19] We draw on school-level data from fall 2018 and 2021, including grade 3-8 enrollment overall; the locale of the school (urban, suburban, rural, and town); and the total staff in the school.
- The Longitudinal School Demographic Dataset[20] combines data from the CCD with other data sources to produce estimates of school and district racial and economic composition that are less systematically error-prone than the raw CCD data. We draw on school-level free- and reduced-price lunch (FRPL) eligibility rates and racial composition data from fall 2017, 2018, and 2021.
- The Return to Learn (R2L) tracker, assembled by the American Enterprise Institute (AEI), includes weekly district-level data on mode of instruction (in-person, hybrid, or remote) from August 2020 through June 2021 for 98 percent of enrollment in U.S. school districts with three or more schools. The R2L data are based on public information released by school districts and define a district as remote if no students older than first grade had an in-person option. We take the average weekly value from the week of September 7, 2020, through the week of June 7, 2021, the time period during which 95%+ of included districts have available data.
- The COVID-19 School Data Hub (CSDH) tracks whether a school or district was remote, hybrid, or in-person in 48 states throughout the 2020-21 school year. The CSDH data are based on a survey of state education agencies, and as a result, the CSDH data vary substantially by state in terms of frequency (ranging from weekly to semesterly) and unit (district or school) of available data. The

[16] We do not restrict to districts with 2022 data available. Note that some of these school districts are now defunct (for example, because they merged with another district). We use the NCES ID as the district identifier and do not attempt to track student populations when the NCES ID changes.
[17] A cohort is complete if estimates are available for all grade-year combinations for the cohort. For example, a cohort that was in 3rd grade in 2011 must have a 4th grade estimate in 2012, a 5th grade estimate in 2013, and so on until 8th grade in 2016.
[18] For all county-level data sources, we assign each district the value for the county in which the district had the highest enrollment.
[19] The CCD data can be accessed at this link: https://nces.ed.gov/ccd/files.asp.
[20] For more details, see https://segindex.org. Data are not yet available for download; a pre-release version of the data was provided to our team.

CSDH data define a district as remote if "all or most" students participated in virtual schooling. We take the average value from October 2020 through May 2021,[21] the months in which all states have available data.[22]

- The COVID-19 Trends and Impact Surveys (CTIS) was a serial cross-sectional, daily survey designed by Carnegie Mellon University and other academic collaborators, implemented in partnership with and through the Facebook platform, and approved by the Institutional Review Board at Carnegie Mellon University and the University of Maryland. It ran continuously for active users of the social media platform that were 18 years of age and older from April 6, 2020 through June 25, 2022 (CTIS, 2022; Salomon et al., 2021). The survey data includes weights reflecting demographic distributions at the state level and adjusting for coverage and non-response biases and were calculated using a two-stage process: (1) inverse propensity score weighting to account for non-response bias, and (2) post-stratification weighting to adjust the Facebook user age and gender distribution to that of the general population (Barkay et al., 2020). More technical details on the survey instrument, sampling design, and weighting methodology can be found in Salomon et al. (2021). For this study, each respondent's Federal Information Processing Standard (FIPS) county code was used to calculate county-level aggregates for each period, where we included participants who: (1) were surveyed from April 2020 through May 2021 (for period 1), and from June 2021 to March 2022 for (period 2), and (2) belonged to counties in the SEDA data.[23] We construct a variety of county-level measures from the CTIS, including measures of instructional modality, unemployment, impacts of COVID on daily life, COVID precautions taken, and anxiety and depression. We constructed period-specific and overall values across both periods by taking month-county averages and then averaging across months. A full list of the measures and survey questions used to create these measures is provided in Appendix Table A3.
- The American Community Survey (ACS) data, collected by the U.S. Census Bureau, provides demographic information about residents living in a school district. We use the following data from the ACS 2015-2019 5-year sample, retrieved from the EDGE data system:[24] the percent of children with both computer and high-speed internet access; and the proportions of adults aged 65+ and of children aged 5-18 living in the district.
- The United States Joint Economic Committee's Social Capital Project provides county-level data on community health and institutional health.[25] The community health subindex combines the number of non-religious non-profits per 1,000 residents with the number of religious

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[21] Most schools reopened for the 2022 school year so there was not much variability in that year. Therefore, we use the 2021 school year data to capture the variability in instructional modality across the two years.
[22] Because the frequency of this data varies, we weight each day equally in calculating the percentage of the school year in each learning mode category.
[23] While some CTIS questions were asked throughout the whole period of study (April 2020 - March 2022), the questionnaire evolved along with public health concerns and priorities, and certain questions were either added after April 2020 or removed before June 2022. In particular, items related to schooling were added in November 28, 2020 (survey Wave 5) and kept until the end of the survey. Therefore, county aggregates for period 1 do not cover April-October 2020. We omitted counties that had fewer than 100 respondents across the study period from the analysis, following CTIS data privacy guidelines.
[24] The EDGE data system can be accessed at this link: https://nces.ed.gov/Programs/EDGE
[25] The JEC data is retrievable from: https://www.jec.senate.gov/public/index.cfm/republicans/socialcapitalproject

congregations per 1,000 residents. The institutional health subindex combines the presidential election voting rate in 2012 and 2016 with the mail-back Census response rate.[26]

- The Opportunity Insights Social Capital Atlas and Economic Tracker includes county-level data on social capital and outdoor activity. The social capital measures are derived from Facebook data and include measures of the volunteering rate (the percentage of Facebook users who are members of a group which is predicted to be about 'volunteering' or 'activism' based on group title and other group characteristics), the civic organizations (the number of Facebook Pages predicted to be 'Public Good' pages based on page title, category, and other page characteristics, per 1,000 users in the county), the support ratio (the proportion of within-county friendships where the pair of friends share a third mutual friend within the same county), and the clustering (the average fraction of an individual's friend pairs who are also friends with each other) in counties. The outdoor activity measures come from Google GPS data and include information on time spent in retail and recreation locations, as well as grocery stores and pharmacies. The GPS data are provided at the daily level; we take an average across the first two years of the pandemic (March 2020 to March 2022) for each county.
- The USAFacts data, obtained from the COVIDcast Epidata API, includes the daily COVID death rate per 100,000 residents. We average this value over the first two years (March 2020 to March 2022) of the pandemic for each county.
- The Safegraph data, obtained from the COVIDcast Epidata API, includes the number of daily visits from those using Safegraph's apps to restaurant locations per 100,000 population. We calculate the average for each county across the first two years of the pandemic (March 2020 to March 2022), divided by the average across the year preceding the pandemic.
- The Harvard Voting and Election Science Team (VEST) data, obtained from the Redistricting Data Hub, includes precinct-level results from the 2020 presidential election. The precinct data is aggregated to the district-level for analysis.

From these data sources, we construct and use measures of district characteristics, instructional modality, and eight additional factors that we believe may have affected learning losses during the pandemic. A summary of the individual variables included in the eight factor measures and their scoring coefficients can be found in Appendix Table A4.

District demographic characteristics and control variables. As noted above, we explore two key district characteristics: poverty and racial composition. Our measure of district poverty is the average of the district FRPL rates in fall 2017 and 2018. Our measure of racial composition is the fall 2018 proportion of minority students, calculated as the sum of the proportions of Black, Hispanic, and Native American students. We obtain these data from the Longitudinal School Demographic Dataset.

We develop two sets of control variables. First, we include general demographic controls. This set includes: the log of the fall 2018 grade 3-8 enrollment and fall 2018 proportions of students within a district in rural, town, and suburban schools from the CCD; the 2020 republican vote share in the district

[26] Both indices also include other state-level measures. However, since our analyses are within-state, for our purposes the state-level measures do not contribute to variation in the indices.

from VEST;[27] and the proportions of adults aged 65+ and of children aged 5-18 living in the district from the 2015-2019 ACS.

Second, to adjust for the changes in the enrollment and the racial and economic composition in the district during the pandemic, we control for the change in log grade 3-8 enrollment from fall 2018 to fall 2021; the changes in the proportion of minority students from fall 2018 to fall 2021; and the change in the proportion of students eligible for FRPL in the district between the fall 2017/2018 average and fall 2021. These are calculated from the CCD and Longitudinal School Demographic Dataset data referenced above.

Instructional modality. We use the R2L, the CSDH, and the CTIS data to construct two sets of measures of districts' instructional modality (remote, hybrid, and not-in-person) during 2020-21.[28] The first set of measures are based on a combination of the R2L and CSDH district-level measures of the percent of time the district was remote or hybrid. Each of these measures likely contain some error due to their data collection procedures. The CSDH data was based on surveys of state education agencies, so data quality and interpretation of what constitutes remote, hybrid, and in-person schooling may differ by state.[29] The R2L data was based on public internet sources that in some cases may have been outdated or ambiguous. We combine these two measures under the assumption that this will reduce the measurement error compared to using either individually. To construct the remote and hybrid variables, we take the average of the R2L and CSDH values and use regression to impute the average when either value is missing. For example, if a district is missing R2L values, we regress the R2L/CSDH average value on the CSDH value among districts that have both values and use the prediction from this regression to impute that district's "average value." To construct a measure of "not in-person," we sum the remote and hybrid measures. These are the primary measures of instructional modality used in our analyses in the paper.

The second set of measures are based on all three data sources. An important advantage of the CTIS data over the R2L and CSDH data is that it based on a household survey and is thus a measure of the modality in which students were actually learning, rather than a measure of school policy.[30] A key disadvantage of the CTIS instructional modality data is that it is only available at the county level, rather than the district or school level. Therefore, to construct a measure that takes advantage of the strengths of both the CTIS and the R2L and CSDH data, we use the CTIS data to measure between-county variation and the

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[27] The precinct-level presidential election results were combined with 2019-20 Census EDGE school district boundaries to obtain school district-level voting shares.

[28] Most districts were open for the 2021-22 school year, and thus the 2020-21 data provides the best measure of variability in instructional modality. In September – December 2021, 98 percent of public school students in the NAEP national public school sample were attending school in person. U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, National Assessment of Educational Progress (NAEP) pre-assessment activity data collection (2021–22), https://ies.ed.gov/schoolsurvey/2022NAEPEnrollment_Policies/. In January – June 2022, the percentage of NCES-surveyed schools offering full-time in-person schooling to at least some students ranged from 97 to 100 percent. U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, School Pulse Panel (2021–22), https://ies.ed.gov/schoolsurvey/spp/.

[29] For example, learning model data for the state of Florida was provided at the biannual level; other states provided data as frequently as weekly.

[30] Lupton-Smith et al. (2022) compare CTIS based measures with other measures of in-person schooling during the pandemic, finding general broad agreement but also highlighting the value of household-level measures to account for variation across households within a county or school district.

R2L/CSDH average to capture within-county variation; essentially, we use the R2L/CSDH data to impute district-level measures that are consistent with the county-level estimates from CTIS.[31]

The two sets of measures are highly correlated. The correlation between the percent remote variables is 0.890 (0.850 within states), the percent in-person variables is 0.846 (0.783 within states), and the percent hybrid variables is 0.696 (0.644 within states). Because the R2L/CSDH variable is more straightforward to explain, we use it for our primary analyses. However, we show a version of our baseline analyses in Appendix Table A6 using the CTIS-R2L/CSDH hybrid measure to demonstrate that our results are not sensitive to the measure of remote learning that we use.

Home computer and internet access. We use a single measure of the percentage of children in a district with both computer and high-speed internet access from the 2015-19 ACS.

School resources. We construct a single measure of school resources from the 2018-19 CCD equal to the total staff divided by the total enrollment (e.g., staff-student ratio) in the district.

Social capital. We use principal component analysis (PCA) to combine five social capital measures into a single factor.[32] Specifically, we use the Opportunity Insights data on the volunteering rate, the number of civic organizations, the support ratio, and clustering, and the Joint Economic Committee's Community Health subindex. Higher values on this factor signal more social capital.

Trust in institutions. We use the Institutional Health subindex from the United States Joint Economic Committee to proxy for trust in institutions. This subindex is a weighted average of three factors: voter participation rates in the 2012 and 2016 presidential elections (averaged over the two years), the rate at which residents returned the 2010 decennial census questionnaire through the mail, and the share of adults with "great" or "some" confidence in corporations, the media, and public schools. Since the third factor was only available at the state level and because we are focusing on within-state differences, the variation we use relies on county-level differences in voter participation and decennial census questionnaire returns (Social Capital Project, 2018). Higher values on this index signal greater trust in institutions.

Pandemic employment. We use a single measure of county-level unemployment from the CTIS that is the percent of respondents not working for pay, among those with a child at home, calculated for each county as the average of their monthly averages from April 2020 through March 2022. Note that this measure differs from traditional unemployment measures because it does not limit to individuals who are actively seeking employment. It includes those who are not working and not seeking employment.

Deaths from COVID-19. We used a single measure of county-level COVID-19 death rates per 100,000 residents from March 2020 to March 2022 from the USAFacts database.

COVID-19 disruptions to normal life. We used PCA to combine 19 variables from the Safegraph, Opportunity Insights Google, and CTIS data into a single factor that represents COVID-19 disruptions to

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[31] We construct these measures in four steps: (1) Take the average of the R2L and CSDH measures for each district and subtract the county-level mean of this value. (2) Obtain the coefficients from a regression of the CTIS measure on the county-level R2L/CSDH average remote and in-person value. (3) Rescale the county-demeaned R2L/CSDH average based using the coefficients of this regression. (4) Add this rescaled value to the CTIS value.

[32] In all cases where PCA is applied, the resulting factor is the first principal component.

normal life. From the Google data on Opportunity Insights, we use the percent change in time spent at retail and recreation establishments and the percent change in time spent at grocery stores, each relative to January 2020. From Safegraph, we use the percent change in restaurant activity from pre-pandemic to during the pandemic. From CTIS, we use data on the following behaviors: going to market/pharmacy/grocery in the last 24 hours, visiting a bar/restaurant/café in the last 24 hours, seeing an external (not member of the household) person in the last 24 hours, attending a large event in the last 24 hours, and "always" avoiding socializing. We also use CTIS data on the proportion of respondents with children in the household who reported they were vaccinated, usually wore a mask, and were worried about COVID-19. All CTIS measures were calculated among respondents that had a child at home and calculated as averages of month-averages in each of the two CTIS time periods used. Higher values on this factor indicate larger disruptions to normal life.

Anxiety and depression. We used PCA to combine measures from the, including the percentages of respondents that had a child at home who reported being anxious and who reported being depressed in the first or second year of the pandemic. Higher values on this measure indicate higher incidence of anxiety and depression among adults.

Table 1 shows the descriptive statistics for the above demographic, control, and factor measures for the main sample; Appendix Table A2 shows the descriptive statistics for the subgroup samples. In the average district pre-pandemic in our sample, half the students are FRPL-eligible, and a quarter identify as Black, Hispanic, or Native American. Notably, the districts in our sample did experience population changes, both in declines in average enrollment and in the average share of students eligible for FRPL from pre-pandemic to 2022. There was also an average increase between 2019 and 2022 in the proportion of minority students in the average district. While the average changes are relatively small, in some districts the changes were quite substantial and, thus, is it critical to adjust for these in our analyses.

On average, districts spent about 46% of the 2020-21 school year in in-person instruction with the remainder in remote and hybrid instruction. However, the amount of time in remote, hybrid, and in-person instruction varied significantly among the districts in the sample. There is also substantial variation in the eight additional factors explored. The average district in our sample had 0.145 staff per student (within-state SD = 0.034); about 89% of households with kids reported access to computers with broadband (within-state SD = 0.091); a working rate of 0.823 (within-state SD = 0.065); and a COVID-19 death rate of .430 deaths per 100,000 (within-state SD = 0.129).

Within-state correlations among the factor variables are shown in Table 2. In our sample, high-poverty districts tend to also be high-minority districts (r = .645). Both high-poverty and high-minority districts tended to spend more time in remote learning. Notably, the correlation with time spent in remote learning is higher for the percent of minority students (r = .477) than for the FRPL eligibility rate (r = .259). Time spent in remote learning was also strongly correlated with COVID-19 disruptions to normal life (r = .423).

Within states, high-minority schools districts also tended to have fewer adults reporting working during the pandemic (r = -.167), more limited computer/internet access (r = -.274), lower social capital (-.268), lower trust in institutions (r = -.124), and more COVID-19-related disruptions to normal life (r = .422). However, they also tended to have lower reported rates of anxiety and depression (r = -.196).

Notably, some of the factors we explore are strongly correlated within states; this is relevant for our specifications that include all factors. In particular, the rate of employment during the pandemic is strongly positively correlated with local social capital, COVID-19 death rates, and rates of anxiety and depression. It is also strongly negatively correlated with trust in institutions and COVID-19 disruptions to normal life.

Methods

Differential Change Analyses

Correlations. We estimate within-state correlations between each factor and the 2016-19, 2019-22, and differential changes in two steps. First, we estimate a precision-weighted model (using `-metareg-` in Stata) of each outcome variable on state fixed effects; the precision-weights are the standard errors for the outcome variable. From this model, we capture the estimate of the within-state variance, τ^2_{state}. We then estimate the same model with a single factor added and capture the within-state variance after controlling for the factor, τ^2_{factor}. The correlations are calculated using the resulting variance terms, as: $r = \pm\sqrt{1 - \frac{\tau^2_{factor}}{\tau^2_{state}}}$ and signed the same as the coefficient on the factor in the second model. The confidence interval of the correlation is determined by scaling the standard error of the coefficient on the factor to the magnitude of the correlation.

Baseline analyses. We use the differential change in achievement between 2019-22 (relative to the three-year change immediately before the pandemic from 2016-19) as our primary outcome variable. With a few exceptions which we highlight in the Results section, we find similar results using the single change from 2019 to 2022 as our outcome variable. Tables with the simple 2019-22 change as the outcome are shown in the Appendix.

Our first set of analyses focuses on understanding the associations between changes in test scores and district poverty, racial composition, and instructional modality. We fit precision-weighted state fixed-effects regression models of the following form:

$$\widehat{\Delta}_d = \alpha_0 + \alpha_1 FRPL_d + \alpha_2 Minority_d + \alpha_3 Remote_d + \alpha_4 Hybrid_d + \mathbf{\Lambda} + e_d + \epsilon_d, \tag{2}$$

where $\widehat{\Delta}_d$ is the estimated differential change parameter (the unshrunken estimate $\hat{\beta}_{2d}$) in math or reading from Model 1 above; $FRPL_d$ is the average percentage of students in the district eligible for FRPL in fall 2017 and 2018; $Minority_d$ is the average percentage of minority students in the district in 2018; $Remote_d$ is a variable describing the share of the 2020-21 school year that schools were implementing remote instruction; $Hybrid_d$ is a variable describing the share of the 2020-21 school year schools were implementing hybrid instruction; and $\mathbf{\Lambda}$ is a vector of state fixed effects. The first error term in the model, e_d, is the model error, assumed homoscedastic with variance to be estimated; the second error term, ϵ_d, is the estimation error in $\widehat{\Delta}_d$, assumed normally distributed with variance assumed equal to the squared standard error of where $\widehat{\Delta}_d$.

We then test whether there are significant interactions between the proportion of the school year spent in either remote or hybrid instruction ("time spent not in in-person instruction") and both the proportion FRPL and minority in the district. We add these interactions individually and then together. In all models, we demean each of the predictors within state prior to constructing the interaction term to ensure the interactions can be interpreted as within-state associations.[33] Following Abadie et al. (2021), because all of our key covariates vary by district within state and because we are not sampling at the state level, we do not cluster standard errors at the state level. All models are estimated using the `-metareg-` package in Stata.

Based on exploratory analyses, we opt to use the model with the single interaction between instructional modality and percent minority as our primary specification and add control variables, shown in equation (3) below:

$$\begin{aligned}\widehat{\Delta}_d = \alpha_0 + \alpha_1 FRPL_d + \alpha_2 Minority_d + \alpha_3 Remote_d + \alpha_4 Hybrid_d \\ + \alpha_5 (Minority_d \times NotinPerson_d) + \mathbf{AX} + \mathbf{\Lambda} + e_d + \epsilon_d\end{aligned} \tag{3}$$

where $\widehat{\Delta}_d$, $FRPL_d$ $Minority_d$, $Remote_d$, $Hybrid_d$, and $\mathbf{\Lambda}$ are defined as above; $NotinPerson_d$ is the proportion of the school year spent in either remote or hybrid instruction; and $\mathbf{X}$ includes a number of characteristics of the district or the county in which the district is located. We iteratively include two sets of control variables in $\mathbf{X}$: (1) local contextual controls (e.g., district urbanicity, republican vote share, and local age distribution); and (2) population and racial composition change controls (e.g., the changes in enrollment, percent minority, and percent FRPL).

Subgroup analyses. We estimate a variant of equation (2) including both sets of controls separately for all students and the Black, Hispanic, White, Economically Disadvantaged, and Not Disadvantaged subgroups. We do not include the interaction term $(Minority_d \times NotinPerson_d)$ in this specification.

Covariate analyses. To test whether the eight additional factors explain variation in the differential changes, we estimate eight models where we add a single factor, and its interaction with time spent in remote or hybrid learning, to the model in equation (3)—our preferred specification. We also estimate a version of the model with all factors and their interactions with time spent in remote/hybrid learning added simultaneously.

Results

Bivariate Correlations

In Figure 1, we show the within-state bivariate correlations among each of the covariate measures and: (1) the change from 2016-19; (2) the change from 2019-22; and (3) the differential change in achievement from 2019-22 less that from 2016-19 (our primary outcome) in math. Appendix Figure A1 shows the corresponding figure for reading.

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[33] Demeaning with the national sample implicitly assumes that the coefficient on the state means and the interactions among the state means are equal to that on the state-centered variables, an assumption that we found not to be met in these data.

While the change in achievement from 2016-19 is associated with some of the factors explored (top panel), these associations are much smaller than those between the factors and the change from 2019-22 (middle panel). It is not surprising that some relatively stable factors like economic and racial composition are associated with changes in achievement prior to the pandemic. Other factors like remote learning that are highly correlated with demographics, as shown above, may be associated with changes in learning from 2016-19 as a result of omitted variables. By using the differential change as our outcome (bottom panel), we net out any part of the association that would have existed in the absence of the pandemic.

The correlations with the differential change are largely similar in sign to those with the 2019-22 change. The exception is the COVID-19 death rate, which positively correlated with 2019-22 change but negatively correlated with the differential change. The negative correlation, however, is non-significant.

Overall, the bivariate correlations show that districts that had larger 2019-22 and larger differential losses in achievement tended to serve larger shares of poor and minority students. The bivariate correlations with the percent of minority students are stronger than with the percent of students eligible for FRPL. Figure 2 shows the scatterplot of the district-level change in achievement from 2019 to 2022 versus the percent of students eligible for FRPL, by subject. Figure 3 shows the same but with percent of minority students in the district on the x-axis. As evidenced by the fitted line in these plots, districts with larger shares of students eligible for FRPL and minority students suffered larger losses in both subjects than those with few FRPL-eligible and minority students. Districts with larger 19-22 and differential losses also tended to spend more time in remote learning. Figure 4 shows the scatterplot of the change in achievement from 2019 to 2022 vs. the percent time of time in remote or hybrid ("not-in-person") learning. Again, districts that spent more time in remote or hybrid instruction suffered larger losses in math and reading than those that spent more time in-person.

Importantly, there is a lot of variation in losses that these three factors cannot explain. Exploring the eight additional factors we see that districts with larger differential losses in math also have more disruptions to normal life due to the COVID-19 pandemic. In contrast, districts with smaller differential losses in math had higher employment rates, average social capital, institutional trust, and access to broadband. These associations align with our hypotheses. However, school resources, COVID-19 death rates, and anxiety and depression rates are not significant correlated with the differential change in achievement as we had hypothesized.

Baseline Analyses

In Table 3, columns M1 and R1 we use equation (2) to estimate the main effects of percent FRPL, percent minority, percent remote, and percent hybrid on the differential change in math and reading achievement. Districts with higher proportions of FRPL-eligible and minority students had larger losses in math achievement; only the coefficient on FRPL was significant in reading. More time in remote and hybrid learning was also associated with larger losses in both subjects.

When added individually, both the FRPL (M2, R2) and minority (M3, R3) interactions are negative and significant in math (both are negative but not significant in reading). These interactions suggest that not being in-person was differentially worse for high poverty and high minority districts. The R^2 in these models are similar, but the coefficient on the interaction with percent minority is larger than that for percent FRPL. When both interactions are included (M4, R4), neither is significant in either subject. Because of this, we opt to use the model in columns M3 and R3 as our primary specification.

We show these results visually in Figure 5. For the purposes of illustration, we sorted districts into within-state deciles by percent not in-person as well as by within-state quartiles of percent minority.[34] The blue points plot the average learning loss in each decile of percent not in-person for districts in the bottom quartile of percent minority enrollment, with the blue line showing the predicted learning loss for these low-minority districts from a linear regression. The orange points and line show corresponding estimates for high-minority districts in the top quartile of percent minority enrollment. In low minority districts in the bottom decile of not in-person instruction (with less than 10 percent of the year not-in-person,[35] so primarily in-person instruction), students lost roughly a third of grade equivalent in math achievement. The losses were somewhat larger in high minority districts in the bottom decile of not-in-person instruction, about 0.5 grade level equivalents. As the percent of the year spent in remote or hybrid instruction increases, the two lines diverge further, reflecting the fact that the achievement losses were considerably higher in high minority districts among those using not-in-person instruction for a larger share of the year. In the top decile of districts that spent almost the entire year not-in-person, students in high minority districts lost 0.8 grade levels, while students in low minority districts lost roughly 0.45 grade levels. In other words, the consequences of not-in-person instruction were more severe in districts serving large shares of minority students.

Appendix Figure A2 reports results for reading. Although the magnitude of losses was smaller, the pattern of larger losses associated with remote instruction in high minority schools is similar to that observed in math.

In Table 4, we add controls to our primary specification to see if it changes the associations. Columns M3 and R3 are the same as in Table 3. In the columns M5 and R5 we add controls for log enrollment, district urbanicity, 2020 Republican vote share, and local population age distribution. Addition of this set of controls does not substantively change the conclusions. In the final set of columns (M6 and R6), we add the controls for population changes during the pandemic period. Districts with larger decreases in grade 3-8 enrollment had smaller losses on average, suggesting that the apparently better achievement in these districts may have been the result of lower-achieving students leaving the districts or not testing. However, these effects explain only a small portion of between-district variation. We estimate that standard-deviation decrease (10%) in enrollment would lead to a 0.07 grade-level increase in the outcome variable. While the change in log enrollment and change in racial composition are significant predictors of differential losses (losses are larger in districts with smaller enrollment declines and larger increases in the proportion of minority students), the key coefficients on district poverty, racial composition, and instructional modality are robust to their inclusion.

In Appendix Table A5, we report the results of our baseline specifications using the raw 2019-22 score change as the outcome variable. Results are similar, although the negative effect of remote schooling is

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[34] To match our regression results, we calculated the quantiles of share of minority students and not in-person learning within-state. We then added the national mean to the x-axis to make the within-state level of not in-person schooling comparable to a national scale.
[35] Note that deciles were defined based on time not-in-person relative to other districts in the state, and the percent not-in-person in the x-axis is an adjusted mean after removing variation across states.

stronger in reading and the coefficient on Republican vote share is positive in both subjects. In Appendix Table A6, we report the results using our alternate measure of schooling modality using CTIS survey results. Results are similar again, with a stronger association between remote learning and losses in reading.

Subgroup Analyses

Because the results in Tables 3 and 4 are all estimated with district-level data, we can only conclude that losses were larger in higher minority, lower income districts, and that those districts were hit harder by remote learning. However, those between-district relationships could partly be the result of disparate impacts within district: were Black, Hispanic, and poor students within districts more negatively impacted by remote and hybrid learning? In other words, did gaps also widen by racial and economic subgroup within district?

In Figure 6, we show the average differential change in achievement for subgroups within districts. For districts with estimates with both subgroups (for example, White and Black students), we create deciles for the overall district achievement change. We then plot the average score changes for both subgroups within the overall district deciles. Black and White students in the same district lost approximately the same amount, as did Hispanic and White students. Non-poor students lost slightly more than poor students, though the average difference is small. Appendix Figure A3 shows the same charts for reading, with similar results.

Next, we investigate whether Black, Hispanic, and poor students were differentially affected within districts by remote and hybrid learning, or by any of the other coefficients in our baseline model. In Table 5, we report the coefficients from our subgroup model specifications. This model includes the main effects of FRPL, percent minority, instructional modality, and all controls. The first column is estimated with the analysis sample for the baseline analyses, with all students in the district. Results are similar to those for M6 in Table 4, which included the interaction term. In the next three columns, this model is estimated separately for all, White, and Black students in the sample of districts with estimates for both White and Black students (N = 1936). The losses in achievement were similar for Black and White students and the coefficients on poverty status, remote schooling, hybrid schooling, and percent minority were statistically indistinguishable from one another. Because the covariates are all measured at the district level, the difference in coefficients is analogous to what we would have gotten regressing the difference in White-Black outcomes within districts on each of the district-level characteristics.

The second set of columns reports the coefficients for districts with both White and Hispanic subgroups. Again, we could not reject the hypothesis that the coefficients were the same—that the White-Hispanic differences did not widen more in districts that remained closed for longer periods. In the third set of columns in Table 5, we report the coefficients for districts with both economically disadvantaged and non-disadvantaged subgroups. Again, we see a similar set of relationships for both subgroups with few exceptions.

The results in Figure 6 and Table 5 strongly imply that the mechanism by which the pandemic affected student achievement operated at the district and/or community level—not within districts. In other words, the cause of achievement loss was likely due to district level differences (such as school resources, the quality of remote instruction, or the level of disruption in district classrooms) or to community-level factors (such as the degree of normalcy in social and economic interactions, local COVID death rates, or other factors that would have affected most households in a community). Household factors which vary among subgroups within a district appear to have been less important in shaping learning losses.

Explaining Losses: Community Factors

To investigate possible community-level contributors to learning loss, we add to the primary specification with controls (M6 and R6) model a series of community-level factors. Specifically, we fit a series of models like models M6 and R6; in each model, we include one of the 8 community-level factors and its interaction with the percent of the 2020-21 academic year that schools used not-in-person instruction. In Table 6, we report the coefficient on the community-level factor and the coefficient on the interaction term in the same row.

We find that the losses in math were larger in counties with higher death rates: a unit change in the number of daily COVID deaths per 100,000 residents was associated with a 0.18 grade-equivalent loss in math achievement (it was non-significant in reading). In math, learning losses associated with the share of the school year spent not in person were also larger in communities with higher death rates. There was no significant interaction in reading.

The negative impact of higher death rates on achievement depends on the difference-in-difference specification. As reported in Figure 1, COVID death rates were *positively* associated with the change in achievement from 2019-2022. But they were even more positively associated with the change in achievement from 2016-2019. Given that COVID death rates could not have affected the 2016-19 change, the positive association with 2016-19 changes likely reflects the association of COVID death rates with some other variable that is associated with increases in test scores. Appendix Table A7 mirrors Table 6 but uses the simple 2019-22 change as the outcome variable. In these models, COVID death rates are positively associated with test score changes, even controlling for the other variables in the model. The difference-in-difference outcome, by implicitly controlling for other stable characteristics of districts, yields a negative coefficient on COVID death rates.

A one standard deviation increase in the index of COVID-19 disruptions to normal life was associated with a 0.06 of grade level loss in math achievement (and 0.04 grade levels in reading achievement). As reflected in the non-significant coefficients on the interaction terms, we did not see that the losses associated with the share of the year schools were in person were any larger in places with more disruptions to normal life—nor did we expect this interaction to be significant.

In districts where a greater percentage of households with children had access to a computer and broadband, achievement losses were smaller in math: a 10 percentage point difference in having both a computer and broadband was associated with a 0.032 smaller achievement loss. However, the interaction with remote/hybrid schooling—which we expected to be positive—was not statistically significant. Although we have controlled for the percent of students eligible for FRPL, we suspect the direct relationship may reflect unmeasured differences in socioeconomic backgrounds. If broadband access were truly a key mechanism for the loss, we would have expected broadband access to be especially impactful where schools were remote for longer.

In counties with higher trust in public institutions (as reflected in higher response rates to the 2020 U.S. Census and voting rates), we see evidence that the loss in achievement was smaller in math (non-significant in reading). Moreover, as reflected in the interaction term, the counties with higher trust had, on average, smaller losses when schools were not offering in-person learning in both math and reading.

There was no direct effect of adult anxiety and depression on achievement losses; however, in math, there was a significant interaction between reports of anxiety and depression and time spent not-in-person. The coefficient suggests losses associated with remote/hybrid learning were larger in districts where adults reported higher rates of anxiety and depression. There was no relationship in reading.

Similarly, pandemic employment among adults with children was not related to differential losses in math or reading. However, the interaction term with the share of the year schools were not in person was positive, indicating that losses from remote/hybrid school were smaller in areas where more adults were at home and non-employed.

We did not find that the county level measures of social capital or of school staffing were related to achievement losses, either in math or reading.

In Appendix Table A7, we report the results of a similar exercise using the raw 2019-22 change in test scores. Some results differ with this outcome variable. The coefficient on broadband access, while still positive, is no longer significant in math. The social capital variable has an unexpected negative interaction with not-in-person schooling in math. Trust in institutions has an unexpected negative direct effect in reading. Finally, as noted above, the COVID-19 death rate has an unexpected positive direct effect in math, although the interaction with not in-person schooling is negative.

One of our goals was to understand *why* low-income/high minority districts were more negatively impacted during the pandemic and by remote/hybrid schooling. Thus, in Table 7, we report how these relationships in our primary model with controls changed with the addition of community level factors and their interactions with hybrid/remote schooling. Comparing M6 to the model with all factors, we can see the direct effects of FRPL, remote and hybrid schooling, and percent minority shrink very slightly in math. The interaction term between percent minority and not-in-person schooling is stable across the models. In reading, the conclusions are similar; the inclusion of the factors does not strongly affect these terms in the models.[36]

Thus, while some of the community level factors such as the lack of computer/internet access, COVID death rate, degree of disruption in social and economic interactions, and trust in institutions were associated with achievement losses, none of them seemed to be the primary mechanism for the larger losses we witnessed by income, race, and remote/hybrid schooling.

Will Pandemic-Related Changes in Achievement Persist?

Pandemic-related achievement losses were both larger on average and more variable across districts than what typically occurred in districts in the years leading up to the pandemic. The box plot in Figure 7 shows the distribution across districts in predicted changes in test scores from 2016 to 2019 compared to predicted changes from 2019 to 2022, for both math and reading language arts. The predicted changes are derived from a regression of the change in test scores over each period on the pandemic-related factors included in the regression reported in the final column of Table 7 – thus, these predicted changes

[36] In Appendix Table A8, we show a similar comparison using the 2019-22 score change. Again, coefficients in the base model change only slightly when the factors are included.

in test scores from 2019 to 2022 reflect changes in achievement associated with pandemic-related factors, while the predicted changes from 2016 to 2019 capture any pre-existing (non-pandemic-related) association of test score changes with these factors. In line with our earlier analyses, we have adjusted the predictions to remove state effects so that the variation in the box plot only reflects within-state differences across districts (the figure is similar, with somewhat wider dispersion, if we do not adjust for state).

Two facts are apparent in Figure 7. First, as noted earlier, average declines in test scores were larger between 2019 and 2022 than they were between 2016 and 2019, particularly for math. In addition, the declines were much more variable across districts during the pandemic. For example, while roughly half of districts saw a pandemic-related decline in math scores of between one-third and two-thirds of a grade level, districts in the top decile of pandemic-related achievement losses only saw an average loss of 0.17 grade levels in math, while districts in the bottom decile experienced an average loss of 0.89 grade levels in math. Overall, the variance in predicted changes in math test scores associated with pandemic-related factors was roughly five times higher in 2019-2022 than in 2016-2019, and for reading was roughly three times higher (see Figure 8).

It remains to be seen whether the achievement losses suffered during the pandemic will persist or gradually disappear over time —for instance, because "children are resilient" or because district test score changes (like student test scores) simply include a lot of measurement error and "regress to the mean." To explore whether large changes in achievement stayed with a cohort in later grades, we used annual district-level scores by grade from 2009-2019 to identify districts with test-score changes in the top and bottom decile in each grade, e.g., districts that had unusually strong test score growth between fourth grade one year and fifth grade the next year (for example, due to a particularly strong curriculum or group of teachers in fifth grade).[37] We then plotted the mean achievement for cohorts in these districts (relative to the grade before the change) in the grades before and the grades afterwards. To minimize mean reversion due to estimation error, we limited the sample to districts with at least 100 tested students per grade and ranked each cohort using average test-score growth among cohorts from the same district and in those grades but from other years (a "leave-one-out" estimator).

The results are reported in Figure 9.[38] In every grade, cohorts in the top and bottom decile experienced large changes in test scores: The average increase in the top decile is about 0.5 grade levels and the average decline in the bottom decile is about -0.5 grade levels. Following a large decline, test scores remain well below where they were in prior grades, and following a large increase, test scores remain well above where they were in prior grades. Through eighth grade there is no evidence that test scores had recovered. Districts in the bottom decile experienced below-average test-score growth in these

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[37] Districts in the top and bottom decile tend to be smaller districts. When we rank districts into top and bottom quartiles (which includes more large districts) the changes in test scores are smaller but similarly persistent to what we find using deciles.

[38] Similar results for reading scores are in Appendix Figure A4. One factor which could artificially produce persistence in scores would be a district-level shift in demographics that occurred in a particular grade. For instance, if students left the district to attend private middle schools, the district may suddenly have fewer high-income students. However, the results in Figure 9 are very similar when we adjust test scores for changes in the district's percent of students who were Black, Hispanic, Asian or Native American as well as the percent of students receiving free or reduced-price lunch.

grades over many years yet were unable to help students recover in subsequent grades. Therefore, we should not assume that the pandemic-related losses will soon disappear as a matter of course.

The evidence presented in this section suggests that pandemic-related achievement losses were large and variable across districts, and we should expect that these pandemic-related achievement losses could persist for many years if nothing is done to reverse the losses.

Discussion

The evidence we provide in this paper adds to the growing number of studies documenting the learning losses resulting from the COVID-19 pandemic. There are four key points from our findings worth noting.

First, pandemic-related learning losses are historic in magnitude and highly variable among communities. Among the districts we explored, only a handful of districts experienced learning losses greater than a quarter of a grade level in math during the three year period immediately before the pandemic. The *average* math learning loss from 2019 to 2022 was nearly twice that size. In reading, average learning losses were substantially larger (by about 0.1 grade levels) between 2019 to 2022 than between 2016 and 2019. Moreover, while nearly all districts experienced some learning loss, the range of these losses were highly variable—from near zero to an entire grade level. There was no single pattern of impacts; districts are in very different positions as they emerge from the pandemic.

Second, as others have reported, we also find that scores declined more in high poverty and high minority districts; and in districts that spent more time in remote and hybrid instruction during the 2020-21 school year. Undoubtedly, in-person learning is important for student achievement. But there are many potential mechanisms—differential attendance, engagement with classmates and teachers, motivation, among others. Moreover, teachers were strongly affected by the pandemic—teachers reported higher levels of depression, anxiety, and isolation than other professionals, with teachers in remote settings reporting higher levels of each than teachers in in-person settings (Kush et al., 2022). In so much as these factors affected their teaching, it may have disproportionately affected students in remote classes. We cannot speak to these in this study. However, it is important to note that in the research on pandemic learning losses (Domina et al., 2022) and our study, there is substantial variation in learning losses not explained by instructional modality. Notably, there were districts that spent a lot of time in remote learning that had small losses and districts that spent a lot of time in-person that had large losses.

Third, perhaps surprisingly, we find that the associations between learning loss and district poverty, racial composition, and instructional modality were similar for different subgroups of students within districts—Black, Hispanic, White students and economically disadvantaged and not disadvantaged students. This suggests that the differences in learning losses are not driven by differences in family resources, but by differences in district and community-level factors.

We found that students appear to have been affected by community shutdowns; in general, the more curtailed normal life was in a community, the larger the losses. These closures may have sent a message to kids that the world is not safe, which might affect their own mental health, motivation, and engagement in learning. Community-level death rates also were significantly related to learning losses in math. While this may have had individual effects, if someone in a child's or teacher's family died or was sick, higher death rates at the community level may have similarly made children feel unsafe. Losses were smaller and learning losses associated with remote and hybrid instruction were smaller in communities reporting higher trust in institutions; this may be an indicator of the extent to which a community trusted/supported schools and decisions. Additionally, learning losses associated with remote and hybrid instruction were larger in communities with higher employment rates. These suggest that remote learning may have been particularly difficult when adults were less able to help students, as a result of employment obligations. There is also suggestive evidence, in math, that learning losses related to remote and hybrid instruction were larger in places where adults reported higher levels of anxiety and depression. In such cases, adults may not have been able to support children as fully when learning from home.

Unfortunately, none of the community factors we identified explain a large share of the variation in losses or identify the mechanism by which school closures had larger impacts in high minority communities.

Fourth, evidence shows that past shocks to student achievement have persisted. Although we cannot speak to the mechanisms driving this persistence in our analyses, one hypothesis is that fixed characteristics of districts—such as their curricula, their teaching force, and their school calendar—determine the pace of learning. Especially in math, a curriculum is a prescribed sequence of concepts and lessons which build on one another. When learning is disrupted by a severe flu season or a weak teaching team in a specific grade and year, those teaching in the subsequent grade must pick up wherever the prior grade left off. The same applies when there is a positive shock to achievement—the subsequent grade can start ahead. Although it is theoretically possible to rearrange topics or reduce the time spent on less crucial ones, it is difficult to coordinate the actions of thousands of teachers—and likely impossible to do so on short notice. Thus, it seems that accelerating learning following a disruption is difficult. Although there may be positive or negative shocks in any given year, the underlying pace of learning may be determined by a set of factors which are hard for districts to adjust in the short term.

One reason for hope is that there has been some suggestive evidence of early rebounding this time. Lewis and Kuhfeld (2022) compared achievement growth for roughly 7 million students in more than 22,000 schools during a pre-COVID period—the three school years from 2016-17 through fall 2019—and during the period including the COVID pandemic—the three school years from 2020-21 through fall 2022. Relative to their pre-pandemic comparison group, students who were in second through seventh grade were 0.23 and 0.11 standard deviations behind their pre-pandemic peers in math and reading respectively in the fall of 2021.[39] Student learning was slightly faster during the 2021-22 school year and the losses during the summer of 2022 were slightly smaller than years past. As of fall 2022, students had made up 25 percent and 10 percent of the ground lost since fall 2021 in math and reading respectively.[40] It remains to be seen if that accelerated learning continues—or flattens out, as we saw in the decade before the pandemic.

Using federal relief dollars, many districts invested in supplemental instruction, such as tutors and extra periods of math or reading instruction, during the 2021-22 school year and they expanded summer

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[39] The magnitude of the NWEA losses are very similar to the losses on the NAEP on which our estimates are based. For instance, the 2019-22 losses on the 8th grade NAEP assessment were 0.20 standard deviations in math and .08 standard deviations in reading. On the 4th grade NAEP, the losses amounted to 0.15 standard deviations in math and 0.08 standard deviations in reading.

[40] This is based on Figure 2 from Lewis and Kuhfeld (2022) averaging across grades.

school offerings in the summer of 2022. About 40 percent of school districts and charter organizations nationally have been implementing some form of tutoring (Jordan et al., 2022). Pre-pandemic research implied that a high dosage tutoring program (3 sessions per week, with groups of 4 or fewer students for an academic year) generated an effect size of 0.38 standard deviations—or roughly a grade equivalent in our metrics (Nickow et al., 2020).

These supplemental efforts are important; however, unlikely to be sufficient to fully recover. Given recruitment and scheduling challenges, districts have not been able to serve as many students and with the number of tutoring sessions they had planned (Carbonari et al., 2022). Back of the envelope calculations suggest that even if a district were able to deliver a high-quality tutoring program to 10 percent of its students, that intervention would lead to a 0.1 grade equivalent improvement in average scores in a district—a small effect relative to the size of the learning losses in many districts.

The question then becomes: Where do we go from here?

It seems clear that we need to approach recovery as an on-going effort. To fully recover, districts will need to continue to make concerted investments in student learning over the coming years.

In addition to the high dosage tutoring, research suggests that summer programs can be effective. For instance, the National Summer Learning Project found that 3 hours of academic programming during a 5-week summer program resulted in a 0.08 standard deviation gain in math achievement—about 0.25 grade equivalents, using our metrics (Augustine et al., 2016). Another option to increase instructional time would be to add an extra period of math or reading instruction. Studies of "double-dose" Algebra programs in Chicago and Miami have estimated impacts of 0.2 standard deviations—or roughly a half a grade level (Nomi & Allensworth, 2009; Taylor, 2014).

The expiration of the last batch of federal relief dollars in September 2024 could jeopardize the continued recovery. The hardest hit districts are likely to need state and local funds to continue. Successful efforts, such as Dallas Independent School District paying teachers in 41 schools to add five weeks of instruction,[41] have only been possible because of such funding. Federal and state supports need not be limited to funding. Other resources, such as guidelines on effective interventions and programs that increase access to qualified tutors, will be helpful.

Ultimately, the success of the recovery will depend not just on funding and guidance but on parental demand. Few district leaders are going to propose potentially controversial steps—such as extending the school year—in the face of parent and school board opposition. On that score, the evidence is less encouraging. Surveys imply that families are ill-informed about the magnitude of student losses. In the fall of 2022, a Pew survey showed that only a quarter of parents thought their child remained behind where they should be in school (Pew Research Center, 2022). An Education Next survey further found that less than one tenth of parents acknowledged that their children were still behind and were concerned about whether their children would catch up (Peterson et al, 2022). Parents see that their children have resumed learning, but they have little direct knowledge of whether their children are achieving at the level they would have been if not for the pandemic. For instance, states typically report score percentiles based on current distributions—not pre-pandemic distributions. Unfortunately, the result has been low student and family take up. For example, when Los Angeles Unified School District added 2 optional days

[41] https://www.dallasisd.org/Page/74537

over the 2022 winter break, only 11 percent of students signed up.[42] Given the disincentives facing state and local education agency leaders to call attention to the crisis that seems unlikely to change. Once the federal dollars run out, further progress will require gubernatorial or mayoral leadership, as well as engagement from the advocacy community. In its absence, the sharp increase in inequality that occurred during the pandemic will become permanent.

[42] https://www.latimes.com/california/story/2022-12-07/about-1-in-9-los-angeles-students-will-attend-extra-learning-days-what-happened

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. M. (2023). When Should You Adjust Standard Errors for Clustering? *The Quarterly Journal of Economics*, *138*(1), 1–35. https://doi.org/10.1093/qje/qjac038

American Enterprise Institute. (2022). *Return to Learn Tracker Data*. Version 45f.

Ananat, E. O., Gassman-Pines, A., Francis, D., & Gibson-Davis, C. (2011). *Children Left Behind: The Effects of Statewide Job Loss on Student Achievement* (Working Paper No. 17104). National Bureau of Economic Research. https://doi.org/10.3386/w17104

Augustine, C. H., McCombs, J. S., Pane, J. F., Schwartz, H. L., Schweig, J., McEachin, A., & Siler-Evans, K. (2016). *Learning from Summer: Effects of Voluntary Summer Learning Programs on Low-Income Urban Youth*. RAND Corporation. https://www.rand.org/pubs/research_reports/RR1557.html

Barkay, N., Cobb, C., Eilat, R., Galili, T., Haimovich, D., LaRocca, S., Morris, K., & Sarig, T. (2020). *Weights and Methodology Brief for the COVID-19 Symptom Survey by University of Maryland and Carnegie Mellon University, in Partnership with Facebook* (arXiv:2009.14675). arXiv. https://doi.org/10.48550/arXiv.2009.14675

Betthäuser, B. A., Bach-Mortensen, A. M., & Engzell, P. (2023). A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic. *Nature Human Behaviour*, *7*(3), Article 3. https://doi.org/10.1038/s41562-022-01506-4

Bielinski, J., Brown, R., & Wagner, K. (2021). *No Longer a Prediction: What New Data Tell Us About the Effects of 2020 Learning Disruptions* [White paper]. Illuminate Education. https://www.illuminateed.com/wp-content/uploads/2021/06/LearningLoss_2021_Update_FB_031221.pdf

Blume, H. (2022, December 7). Only 1 in 9 Los Angeles students will attend extra learning days. What happened? *Los Angeles Times*. https://www.latimes.com/california/story/2022-12-07/about-1-in-9-los-angeles-students-will-attend-extra-learning-days-what-happened

Camp, A. M., & Zamarro, G. (2022). Determinants of Ethnic Differences in School Modality Choices During the COVID-19 Crisis. *Educational Researcher*, *51*(1), 6–16. https://doi.org/10.3102/0013189X211057562

Carbonari, M. V., Davison, M., DeArmond, M., Dewey, D., Dizon-Ross, E., Goldhaber, D., Hashim, A., Kane, T. J., McEachin, A., Morton, E., Patterson, T., & Staiger, D. O. (2022). *The Challenges of Implementing Academic COVID Recovery Interventions: Evidence from the Road to Recovery Project*. CALDER. https://caldercenter.org/sites/default/files/CALDER%20WP%20275-1222.pdf

Chetty, R., Friedman, J. N., Stepner, M., & Team, T. O. I. (2020). *The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data* (Working Paper No. 27431). National Bureau of Economic Research. https://doi.org/10.3386/w27431

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., Laguna-Muggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., … Wernerfelt, N. (2022a). Social capital I:

Measurement and associations with economic mobility. *Nature*, *608*(7921), Article 7921. https://doi.org/10.1038/s41586-022-04996-4

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., Laguna-Muggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., … Wernerfelt, N. (2022b). Social capital II: Determinants of economic connectedness. *Nature*, *608*(7921), Article 7921. https://doi.org/10.1038/s41586-022-04997-3

COVID-19 means more students not learning to read. (2021). [Research brief]. Amplify Education.

COVID-19 Provisional Counts—Health Disparities. (n.d.). Center for Disease Control and Prevention, National Center for Health Statistics. Retrieved April 14, 2023, from https://www.cdc.gov/nchs/nvss/vsrr/covid19/health_disparities.htm#RaceHispanicOrigin

COVID-19 School Data Hub. (2023a). *All School Learning Model Data (Version 3/8/23)*. Accessed March 22, 2023. https://www.covidschooldatahub.com/data-resources.

COVID-19 School Data Hub. (2023b). *All District Learning Model Data (Version 2/28/23)*. Accessed March 22, 2023. https://www.covidschooldatahub.com/data-resources.

CTIS. (2022). *Methodology Report for the COVID-19 Trends and Impact Survey* (Methodology Report Version 1). The Delphi Group at Carnegie Mellon University and University of Maryland Social Data Science Center COVID-19 Trends and Impact Survey, in partnership with Meta. https://dataforgood.facebook.com/dfg/resources/CTIS-methodology-report

Dee, T. S. (2023). *Where the Kids Went: Nonpublic Schooling and Demographic Change during the Pandemic Exodus from Public Schools* [Brief]. Urban Institute. https://www.urban.org/research/publication/where-kids-went-nonpublic-schooling-and-demographic-change-during-pandemic

Domina, T., Hashim, A., Kearney, C., Pham, L., & Smith, C. (2022). *COVID-19 and the System Resilience of Public Education: A View from North Carolina* [Brief]. Urban Institute. https://www.urban.org/research/publication/covid-19-and-system-resilience-public-education-view-north-carolina

Domingue, B. W., Dell, M., Lang, D., Silverman, R., Yeatman, J., & Hough, H. (2022). The Effect of COVID on Oral Reading Fluency During the 2020–2021 Academic Year. *AERA Open*, *8*, 23328584221120256. https://doi.org/10.1177/23328584221120254

Ettman, C. K., Fan, A. Y., Subramanian, M., Adam, G. P., Badillo Goicoechea, E., Abdalla, S. M., Stuart, E. A., & Galea, S. (2023). Prevalence of depressive symptoms in U.S. adults during the COVID-19 pandemic: A systematic review. *SSM - Population Health*, *21*, 101348. https://doi.org/10.1016/j.ssmph.2023.101348

Fahle, E., Reardon, S. F., Shear, B., Ho, A., Saliba, J., & Kalogrides, D. (2023). *Stanford Education Data Archive Technical Documentation: SEDA2022 2.0*. http://purl.stanford.edu/db586ns4974.

Fahle, E., Kane, T. J., Patterson, T., Reardon, S. F., & Staiger, D. O. (2022). *Local Achievement Impacts of the Pandemic* [Research brief]. Education Recovery Scorecard.

https://educationrecoveryscorecard.org/wp-content/uploads/2022/10/Education-Recovery-Scorecard_Key-Findings_102822.pdf

Farrow, D. C., Brooks, L. C., Ribshirani, R. J., & Rosenfeld, R. (2015). *Delphi Epidata API*. https://github.com/cmu-delphi/delphi-epidata.

Gassman-Pines, A., Ananat, E. O., & Fitz-Henley, J., II. (2020). COVID-19 and Parent-Child Psychological Well-being. *Pediatrics*, *146*(4), e2020007294. https://doi.org/10.1542/peds.2020-007294

Goldhaber, D., Kane, T. J., McEachin, A., Morton, E., Patterson, T., & Staiger, D. O. (2022a). *The Consequences of Remote and Hybrid Instruction During the Pandemic* (Working Paper No. 30010). National Bureau of Economic Research. https://doi.org/10.3386/w30010

Goldhaber, D., Kane, T. J., McEachin, A., & Morton, E. (2022b). *A Comprehensive Picture of Achievement Across the COVID-19 Pandemic Years: Examining Variation in Test Levels and Growth Across Districts, Schools, Grades, and Students* (CALDER Working Paper No. 266–0522). CALDER. https://caldercenter.org/publications/comprehensive-picture-achievement-across-covid-19-pandemic-years-examining-variation

Grossmann, M., Reckhow, S., Strunk, K. O., & Turner, M. (2021). All States Close but Red Districts Reopen: The Politics of In-Person Schooling During the COVID-19 Pandemic. *Educational Researcher*, *50*(9), 637–648. https://doi.org/10.3102/0013189X211048840

Intersession Schools. (n.d.). Dallas ISD. Retrieved May 4, 2023, from https://www.dallasisd.org/Page/74537

Jack, R., Halloran, C., Okun, J., & Oster, E. (2022). *Pandemic Schooling Mode and Student Test Scores: Evidence from U.S. School Districts*. https://emilyoster.net/wp-content/uploads/MS_Updated_Revised.pdf

Jordan, P. W., DiMarco, B., & Toch, T. (2022). *An Analysis of Local School Districts' Ambitious Post-Covid Tutoring Plans* [Explainer]. FutureEd. https://www.future-ed.org/an-analysis-of-local-school-districts-ambitious-post-covid-tutoring-plans/

Klinenberg, E. (2002). *Heat Wave: A Social Autopsy of Disaster in Chicago*. University of Chicago Press.

Kogan, V., & Lavertu, S. (2021). *How the COVID-19 Pandemic Affected Student Learning in Ohio: Analysis of Spring 2021 Ohio State Tests*. The Ohio State University, John Glenn College of Public Affairs. https://glenn.osu.edu/sites/default/files/2021-10/210828_KL_OST_Final_0.pdf

Kozakowski, W., Gill, B., Lavallee, P., Burnett, A., & Ladinsky, J. (2021, December). *Changes in academic achievement in Pittsburgh Public Schools during remote instruction in the COVID-19 pandemic* [Slide deck]. Regional Educational Laboratory Program (REL). https://ies.ed.gov/ncee/rel/Products/Region/midatlantic/Resource/100413

Kuhfeld, M., Soland, J., & Lewis, K. (2022). Test Score Patterns Across Three COVID-19-Impacted School Years. *Educational Researcher*, *51*(7), 500–506. https://doi.org/10.3102/0013189X221109178

Kush, J. M., Badillo-Goicoechea, E., Musci, R. J., & Stuart, E. A. (2022). Teachers' Mental Health During the COVID-19 Pandemic. *Educational Researcher*, *51*(9), 593–597. https://doi.org/10.3102/0013189X221134281

Labor force characteristics by race and ethnicity, 2021 (Report 1100). (2023). U.S. Bureau of Labor Statistics. https://www.bls.gov/opub/reports/race-and-ethnicity/2021/home.htm

Lewis, K., & Kuhfeld, M. (2022). *Progress towards pandemic recovery: Continued signs of rebounding achievement at the start of the 2022-23 school year* [Research brief]. NWEA. https://www.nwea.org/research/publication/progress-towards-pandemic-recovery-continued-signs-of-rebounding-achievement-at-the-start-of-the-2022-23-school-year/

Lewis, K., Kuhfeld, M., Ruzek, E., & McEachin, A. (2021). *Learning during COVID-19: Reading and math achievement in the 2020-21 school year* [Research brief]. NWEA. https://www.nwea.org/uploads/2021/07/Learning-during-COVID-19-Reading-and-math-achievement-in-the-2020-2021-school-year.research-brief-1.pdf

Locke, V. N., Patarapichayatham, C., & Lewis, S. (2021). *Learning Loss in Reading and Math in U.S. Schools Due to the COVID-19 Pandemic*. Istation. https://www.istation.com/hubfs/Content/downloads/studies/COVID-19_Learning_Loss_USA.pdf

Lupton-Smith, C., Badillo Goicoechea, E., Collins, M., Lessler, J., Grabowski, M. K., & Stuart, E. A. (2022). Consistency between Household and County Measures of Onsite Schooling during the COVID-19 Pandemic. *Journal of Research on Educational Effectiveness*. https://doi.org/10.1080/19345747.2022.2131660

The Nation's Report Card. U.S. Department of Education. https://www.nationsreportcard.gov/

Nickow, A., Oreopoulos, P., & Quan, V. (2020). *The Impressive Effects of Tutoring on PreK-12 Learning: A Systematic Review and Meta-Analysis of the Experimental Evidence* (Working Paper No. 27476). National Bureau of Economic Research. https://doi.org/10.3386/w27476

Nomi, Takako and Elaine Allensworth. 2009. "'Double-Dose' Algebra as an Alternative Strategy to Remediation: Effects on Students' Academic Outcomes." Journal of Research on Educational Effectiveness 2 (2): 111-148.

Opportunity Insights. (2022). *Opportunity Insights Economic Tracker*. https://www.tracktherecovery.org/.

Oster, E., Jack, R., Halloran, C., Schoof, J., McLeod, D., Yang, H., Roche, J., & Roche, D. (2021). Disparities in Learning Mode Access Among K-12 Students During the COVID-19 Pandemic, by Race/Ethnicity, Geography, and Grade Level—United States, September 2020-April 2021. *Morbidity and Mortality Weekly Report*, *70*(26), 953–958. https://doi.org/10.15585/mmwr.mm7026e2

Parolin, Z., & Lee, E. K. (2021). Large socio-economic, geographic and demographic disparities exist in exposure to school closures. *Nature Human Behaviour*, *5*(4), Article 4. https://doi.org/10.1038/s41562-021-01087-8

Partelow, S. (2021). Social capital and community disaster resilience: Post-earthquake tourism recovery on Gili Trawangan, Indonesia. *Sustainability Science*, *16*(1), 203–220. https://doi.org/10.1007/s11625-020-00854-2

Peterson, Paul E., David M. Houston, Martin R. West (2022) *Survey 2022, Parent Responses*. Program on Education Policy and Government, Harvard Kennedy School. https://www.educationnext.org/wp-content/uploads/2022/08/2022ednextpollparentsurvey.pdf

Pew Research Center American Trends Panel. (2022, September). *Survey of American Parents, Wave 115*. https://www.pewresearch.org/wp-content/uploads/2022/10/W115-topline_COVID-impact-on-K-12-new.pdf

Pier, L., Christian, M., Tymeson, H., & Meyer, R. H. (2021). *COVID-19 Impacts on Student Learning: Evidence from Interim Assessments in California*. https://edpolicyinca.org/sites/default/files/2021-06/r_pier_jun2021.pdf

Reardon, S. F., Kalogrides, D., & Ho, A. D. (2021a). Validation Methods for Aggregate-Level Test Scale Linking: A Case Study Mapping School District Test Score Distributions to a Common Scale. *Journal of Educational and Behavioral Statistics*, *46*(2), 138–167. https://doi.org/10.3102/1076998619874089

Reardon, S. F., Shear, B. R., Castellano, K. E., & Ho, A. D. (2017). Using Heteroskedastic Ordered Probit Models to Recover Moments of Continuous Test Score Distributions From Coarsened Data. *Journal of Educational and Behavioral Statistics*, *42*(1), 3–45. https://doi.org/10.3102/1076998616666279

Reardon, S. F., Fahle, E., Ho, A. D., Shear, B., Kalogrides, D., Saliba, J., & Kane, T. J. (2023). *Stanford Education Data Archive (Version SEDA 2022 2.0)*. http://purl.stanford.edu/db586ns4974.

Reardon, S. F., Ho, A. D., Shear, B., Fahle, E., Kalogrides, D., Jang, H., & Chavez, B. (2021b). *Stanford Education Data Archive (Version 4.1)*. http://purl.stanford.edu/db586ns4974.

Redistricting Data Hub. (2022). *2020 National Precinct Boundary Shapefile*. https://redistrictingdatahub.org/data/download-data/.

Rege, M., Telle, K., & Votruba, M. (2011). Parental Job Loss and Children's School Performance. *The Review of Economic Studies*, *78*(4), 1462–1489. https://doi.org/10.1093/restud/rdr002.

SafeGraph. (2022). *Weekly Patterns Data Set*. https://docs.safegraph.com/docs/weekly-patterns.

Salomon, J. A., Reinhart, A., Bilinski, A., Chua, E. J., La Motte-Kerr, W., Rönn, M. M., Reitsma, M. B., Morris, K. A., LaRocca, S., Farag, T. H., Kreuter, F., Rosenfeld, R., & Tibshirani, R. J. (2021). The US COVID-19 Trends and Impact Survey: Continuous real-time measurement of COVID-19 symptoms, risks, protective behaviors, testing, and vaccination. *Proceedings of the National Academy of Sciences*, *118*(51), e2111454118. https://doi.org/10.1073/pnas.2111454118

Stevens, A. H., & Schaller, J. (2011). Short-run effects of parental job loss on children's academic achievement. *Economics of Education Review*, *30*(2), 289–299. https://doi.org/10.1016/j.econedurev.2010.10.002

Taylor, Eric (2014) "Spending more of the school day in math class: Evidence from a regression discontinuity in middle school," Journal of Public Economics, Volume 117, Pages 162-181. https://doi.org/10.1016/j.jpubeco.2014.06.002.

Thomeer, M. B., Moody, M. D., & Yahirun, J. (2023). Racial and Ethnic Disparities in Mental Health and Mental Health Care During The COVID-19 Pandemic. *Journal of Racial and Ethnic Health Disparities*, *10*(2), 961–976. https://doi.org/10.1007/s40615-022-01284-9

U.S. Census Bureau, American Community Survey. (2019). *2015-19 American Community Survey 5-Year Estimates*.

U.S. Congress, Joint Economic Committee, Social Capital Project. (2018). *The Geography of Social Capital in America*. Report prepared by the Vice Chairman's staff, 115th Cong., 2nd Sess. http://lee.senate.gov/scp/socialcapitalindex.

U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. (2019). *Education Demographic and Geographic Estimates Program (EDGE): Composite School District Boundaries*. https://nces.ed.gov/programs/edge/Geographic/DistrictBoundaries.

U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. (2021-2022). *National Assessment of Educational Progress (NAEP) pre-assessment activity data collection*. https://ies.ed.gov/schoolsurvey/2022NAEPEnrollment_Policies/.

U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. (2022). *School Pulse Panel (2021–22)*. https://ies.ed.gov/schoolsurvey/spp/.

U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Common Core of Data (CCD). (2022a). *Local Education Agency (School District) Universe Survey*. 2017-18 v.1a, 2018-19 v.1a, 2021-22 v.1a.

U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Common Core of Data (CCD). (2022b). *Public Elementary/Secondary School Universe Survey*. 2017-18 v.1a, 2018-19 v.1a, 2021-22 v.1a.

USAFacts. (2022). *Understanding the COVID-19 Pandemic*. https://usafacts.org/issues/coronavirus/.

Voting and Election Science Team. (2020). *2020 Precinct-Level Election Results*. https://doi.org/10.7910/DVN/K7760H, Harvard Dataverse, V40.

Tables

Table 1. Descriptive statistics of variables used in models

Variable	Mean	Overall SD	Within-State SD
Math (19-22 change) - (16-19 change)	-0.515	0.358	0.262
Math 19-22 change	-0.494	0.371	0.300
Math 16-19 change	0.017	0.300	0.266
Reading (19-22 change) - (16-19 change)	-0.102	0.388	0.311
Reading 19-22 change	-0.309	0.333	0.276
Reading 16-19 change	-0.213	0.341	0.296
% Free/Reduced Lunch	0.479	0.222	0.192
% Minority	0.266	0.267	0.219
% in Urban School	0.075	0.239	0.235
% in Rural School	0.432	0.438	0.421
% in Suburban School	0.304	0.428	0.386
% in Town School	0.189	0.351	0.343
% Age 65+	0.176	0.053	0.052
% Age 5-18	0.169	0.035	0.033
2020 Republican Vote Share	0.600	0.182	0.149
Log 3-8 Enrl. Chg.	-0.048	0.102	0.101
% FRL Chg.	-0.020	0.102	0.081
% Minority Chg.	0.012	0.026	0.025
% Remote (R2L/CSDH Avg.)	0.156	0.228	0.178
% Hybrid (R2L/CSDH Avg.)	0.389	0.293	0.235
% In-person (R2L/CSDH Avg.)	0.455	0.358	0.260
% Remote (CTIS Adjusted)	0.364	0.166	0.128
% Hybrid (CTIS Adjusted)	0.258	0.104	0.082
% In-person (CTIS Adjusted)	0.378	0.193	0.130
Home Computer/Internet Access	0.891	0.099	0.091
School Resources	0.145	0.045	0.034
Social Capital	-0.226	0.730	0.609
Trust in Institutions	0.132	0.919	0.434
Pandemic Employment	0.823	0.076	0.065
COVID-19 Death Rate	0.430	0.163	0.129
COVID-19 Disruptions to Normal Life	0.002	0.997	0.719
Anxiety and Depression	-0.029	0.861	0.768

Note: Math score change variable statistics are calculated from the math analysis sample, including 7729 districts. Reading score change variable statistics are calculated from the reading analysis sample, including 7510 districts. All other variable statistics are calculated from the union of the math and reading analysis samples, including 7777 districts.

Table 2. Within-state correlations among factors

	% Free/Reduced Lunch	% Minority	% Remote	% Hybrid	% Not In-person	Home Computer/ Internet Access	School Resources	Social Capital	Trust in Institutions	Pandemic Employment	COVID-19 Death Rate	COVID-19 Disruptions to Normal Life	Anxiety and Depression
% Free/Reduced Lunch	1.000												
% Minority	0.645	1.000											
% Remote (R2L/CSDH Avg.)	0.259	0.477	1.000										
% Hybrid (R2L/CSDH Avg.)	-0.056	-0.003	-0.232	1.000									
% Not In-person (R2L/CSDH Avg.)	0.127	0.324	0.475	0.746	1.000								
Home Computer and Access	-0.456	-0.274	-0.068	0.059	0.007	1.000							
School Resources	0.129	-0.040	-0.052	-0.049	-0.080	-0.154	1.000						
Social Capital	0.137	-0.268	-0.270	-0.068	-0.247	-0.188	0.252	1.000					
Trust in Institutions	-0.353	-0.124	-0.019	0.027	0.011	0.274	-0.054	-0.163	1.000				
Pandemic Employment	0.272	-0.167	-0.278	-0.087	-0.269	-0.239	0.173	0.611	-0.468	1.000			
COVID-19 Death Rate	0.263	-0.025	-0.068	-0.069	-0.110	-0.214	0.108	0.351	-0.363	0.540	1.000		
COVID-19 Disruptions to Normal Life	-0.028	0.422	0.423	0.104	0.384	0.095	-0.127	-0.540	0.077	-0.674	-0.353	1.000	
Anxiety and Depression	0.165	-0.196	-0.167	-0.007	-0.121	-0.114	0.083	0.294	-0.342	0.466	0.257	-0.314	1.000

Note: The instructional modality variables come from the R2L and CSDH combined measure. We demean variables by state before calculating correlations.

Table 3. Baseline specifications predicting the differential change in achievement

	Math				Reading			
	M1	M2	M3	M4	R1	R2	R3	R4
Free/Reduced Lunch	-0.131*	-0.118*	-0.125*	-0.121*	-0.224***	-0.218***	-0.220***	-0.220***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.050)	(0.051)	(0.050)	(0.051)
% Racial Minority	-0.346***	-0.331***	-0.312***	-0.312***	-0.067	-0.060	-0.048	-0.048
	(0.052)	(0.053)	(0.054)	(0.054)	(0.050)	(0.051)	(0.052)	(0.052)
% Remote Schooling	-0.292***	-0.282***	-0.271***	-0.270***	-0.109*	-0.105*	-0.097	-0.097
	(0.051)	(0.052)	(0.052)	(0.052)	(0.049)	(0.049)	(0.050)	(0.050)
% Hybrid Schooling	-0.115***	-0.119***	-0.119***	-0.120***	-0.095**	-0.097**	-0.096**	-0.096**
	(0.034)	(0.034)	(0.034)	(0.034)	(0.032)	(0.033)	(0.032)	(0.033)
Free/Reduced Lunch ×		-0.361*		-0.143		-0.157		-0.024
% Not In-Person School		(0.163)		(0.201)		(0.154)		(0.191)
% Racial Minority ×			-0.382**	-0.312			-0.199	-0.187
% Not In-Person School			(0.136)	(0.167)			(0.129)	(0.160)
State Fixed Effects?	X	X	X	X	X	X	X	X
N	7729	7729	7729	7729	7510	7510	7510	7510
R^2	0.260	0.264	0.265	0.265	0.051	0.051	0.051	0.051

Note: All models are meta-regressions accounting for measurement error in the dependent variable.

Table 4. Preferred specification plus control variables

	Math			Reading		
	M3	M5	M6	R3	R5	R6
Free/Reduced Lunch	-0.125*	-0.213***	-0.251***	-0.220***	-0.279***	-0.329***
	(0.053)	(0.064)	(0.065)	(0.050)	(0.061)	(0.062)
% Racial Minority	-0.312***	-0.186**	-0.157*	-0.048	0.043	0.065
	(0.054)	(0.069)	(0.069)	(0.052)	(0.067)	(0.067)
% Remote Schooling	-0.271***	-0.242***	-0.272***	-0.097	-0.091	-0.112*
	(0.052)	(0.056)	(0.056)	(0.050)	(0.054)	(0.054)
% Hybrid Schooling	-0.119***	-0.111**	-0.116***	-0.096**	-0.095**	-0.103**
	(0.034)	(0.035)	(0.035)	(0.032)	(0.033)	(0.033)
% Racial Minority ×	-0.382**	-0.438**	-0.485***	-0.199	-0.235	-0.263*
% Not In-Person School	(0.136)	(0.137)	(0.137)	(0.129)	(0.130)	(0.130)
Log Enrollment		-0.003	-0.002		0.004	0.004
		(0.010)	(0.010)		(0.009)	(0.009)
% Rural		0.065	0.064		0.074	0.077
		(0.043)	(0.042)		(0.040)	(0.040)
% Town		0.016	0.010		0.022	0.021
		(0.039)	(0.039)		(0.037)	(0.037)
% Suburb		0.004	0.017		0.026	0.033
		(0.035)	(0.035)		(0.033)	(0.033)
2020 Republican Vote		-0.020	0.044		-0.008	0.026
Share		(0.084)	(0.084)		(0.080)	(0.081)
% Age 65+		0.518*	0.336		0.236	0.132
		(0.208)	(0.208)		(0.201)	(0.202)
% Age 5-18		-0.292	-0.370		-0.625*	-0.668*
		(0.301)	(0.299)		(0.289)	(0.288)
Change in Log Enrollment			-0.709***			-0.532***
2019-22			(0.088)			(0.086)
Change in % Racial			-1.459***			-0.352
Minority 2019-22			(0.350)			(0.342)
Change in Free/Reduced			0.206*			-0.013
2019-22			(0.100)			(0.099)
State Fixed Effects?	X	X	X	X	X	X
N	7729	7729	7729	7510	7510	7510
R^2	0.265	0.274	0.349	0.051	0.056	0.079

Note: All models are meta-regressions accounting for measurement error in the dependent variable.

Table 5. Models by race and economic disadvantage subgroups

Math	All	All	White	Black	Diff	All	White	Hispanic	Diff	All	Non-Poor	Poor	Diff
Free/Reduced Lunch	-0.262***	-0.355**	-0.415**	-0.231	n.s.	-0.305***	-0.398***	-0.324**	n.s.	-0.312***	-0.450***	-0.300**	n.s.
	(0.065)	(0.114)	(0.137)	(0.171)		(0.088)	(0.109)	(0.122)		(0.079)	(0.100)	(0.100)	
% Racial Minority	-0.195**	-0.187	-0.188	-0.067	n.s.	-0.287**	-0.162	-0.376**	n.s.	-0.190*	-0.142	-0.110	n.s.
	(0.068)	(0.122)	(0.149)	(0.187)		(0.087)	(0.111)	(0.119)		(0.078)	(0.101)	(0.097)	
% Remote Schooling	-0.294***	-0.302**	-0.408***	-0.282*	n.s.	-0.203**	-0.267**	-0.190*	n.s.	-0.284***	-0.323***	-0.219**	n.s.
	(0.056)	(0.093)	(0.113)	(0.141)		(0.069)	(0.086)	(0.093)		(0.065)	(0.083)	(0.081)	
% Hybrid Schooling	-0.109**	-0.118	-0.127	-0.104	n.s.	-0.076	-0.059	-0.113	n.s.	-0.140***	-0.149**	-0.088	n.s.
	(0.035)	(0.063)	(0.074)	(0.092)		(0.049)	(0.059)	(0.072)		(0.041)	(0.051)	(0.052)	
Log Enrollment	-0.002	-0.039*	-0.017	-0.035	n.s.	-0.025	-0.013	-0.046**	n.s.	-0.006	-0.018	-0.006	n.s.
	(0.010)	(0.017)	(0.020)	(0.024)		(0.013)	(0.016)	(0.017)		(0.012)	(0.015)	(0.015)	
% Rural	0.062	0.037	0.128	-0.022	n.s.	0.143**	0.163*	0.066	n.s.	0.082	0.084	0.084	n.s.
	(0.042)	(0.070)	(0.083)	(0.103)		(0.053)	(0.065)	(0.072)		(0.052)	(0.065)	(0.064)	
% Town	0.015	0.067	0.086	-0.007	n.s.	0.015	0.024	-0.009	n.s.	0.029	0.031	0.039	n.s.
	(0.039)	(0.061)	(0.072)	(0.093)		(0.045)	(0.056)	(0.060)		(0.047)	(0.059)	(0.058)	
% Suburb	0.019	0.044	0.037	-0.005	n.s.	0.032	0.019	0.014	n.s.	0.037	0.056	0.024	n.s.
	(0.035)	(0.043)	(0.052)	(0.064)		(0.038)	(0.048)	(0.048)		(0.041)	(0.052)	(0.050)	
2020 Republican Vote	0.070	-0.018	-0.145	0.112	n.s.	0.065	0.067	0.023	n.s.	0.108	0.134	0.299*	n.s.
Share	(0.084)	(0.145)	(0.177)	(0.219)		(0.105)	(0.130)	(0.142)		(0.098)	(0.123)	(0.125)	
% Age 65+	0.284	0.344	0.175	0.345	n.s.	-0.166	-0.190	-0.083	n.s.	0.102	0.241	-0.302	n.s.
	(0.208)	(0.402)	(0.482)	(0.625)		(0.271)	(0.333)	(0.376)		(0.247)	(0.311)	(0.317)	
% Age 5-18	-0.407	-0.336	-0.390	0.926	n.s.	-0.210	-0.104	0.110	n.s.	-0.558	-0.367	-0.655	n.s.
	(0.299)	(0.538)	(0.662)	(0.824)		(0.390)	(0.489)	(0.534)		(0.354)	(0.450)	(0.454)	
Change in Log Enrollment	-0.699***	-0.664***	-1.008***	-0.718**	n.s.	-0.987***	-1.174***	-0.896***	n.s.	-0.897***	-0.914***	-0.855***	n.s.
2019-22	(0.088)	(0.181)	(0.224)	(0.259)		(0.131)	(0.161)	(0.175)		(0.115)	(0.146)	(0.147)	
Change in % Racial	-1.430***	-1.181	-0.107	-0.951	n.s.	-1.269**	-0.543	-0.841	n.s.	-1.007*	-1.657**	-0.618	n.s.
Minority 2019-22	(0.350)	(0.620)	(0.764)	(0.899)		(0.462)	(0.577)	(0.611)		(0.409)	(0.524)	(0.513)	
Change in Free/Reduced	0.209*	0.045	0.011	0.166	n.s.	0.106	0.042	0.086	n.s.	0.117	0.044	0.164	n.s.
2019-22	(0.100)	(0.190)	(0.238)	(0.267)		(0.154)	(0.195)	(0.203)		(0.147)	(0.188)	(0.183)	
Constant	-0.502***	-0.497***	-0.499***	-0.500***	n.s.	-0.479***	-0.473***	-0.469***	n.s.	-0.451***	-0.529***	-0.480***	***
	(0.008)	(0.013)	(0.015)	(0.020)		(0.010)	(0.012)	(0.014)		(0.009)	(0.011)	(0.012)	
N	7729	1936	1936	1936		3520	3520	3520		5111	5111	5111	
R^2	0.339	0.743	0.175	0.082		0.863	0.185	0.199		0.351	0.124	0.095	

Reading	All	All	White	Black	Diff	All	White	Hispanic	Diff	All	Non-Poor	Poor	Diff
Free/Reduced Lunch	-0.336***	-0.501***	-0.474***	-0.490**	n.s.	-0.357***	-0.332**	-0.265*	n.s.	-0.376***	-0.491***	-0.346***	n.s.
	(0.062)	(0.102)	(0.122)	(0.160)		(0.086)	(0.104)	(0.120)		(0.076)	(0.097)	(0.095)	
% Racial Minority	0.043	0.254*	0.214	0.449*	n.s.	0.075	0.044	-0.073	n.s.	0.054	0.081	0.098	n.s.
	(0.066)	(0.110)	(0.135)	(0.176)		(0.085)	(0.106)	(0.117)		(0.076)	(0.099)	(0.093)	
% Remote Schooling	-0.125*	-0.216*	-0.289**	-0.280*	n.s.	-0.059	-0.101	-0.045	n.s.	-0.119	-0.109	-0.077	n.s.
	(0.054)	(0.084)	(0.102)	(0.131)		(0.068)	(0.082)	(0.091)		(0.063)	(0.080)	(0.077)	
% Hybrid Schooling	-0.101**	-0.085	-0.124	-0.026	n.s.	-0.062	-0.073	-0.114	n.s.	-0.071	-0.082	-0.056	n.s.
	(0.033)	(0.056)	(0.064)	(0.085)		(0.048)	(0.055)	(0.071)		(0.039)	(0.049)	(0.049)	
Log Enrollment	0.004	-0.010	-0.003	-0.004	n.s.	-0.009	0.001	-0.021	n.s.	0.002	-0.027	0.021	*
	(0.009)	(0.015)	(0.018)	(0.023)		(0.013)	(0.015)	(0.017)		(0.012)	(0.015)	(0.015)	
% Rural	0.075	0.115	0.198**	0.112	n.s.	0.125*	0.148*	0.083	n.s.	0.057	0.011	0.102	n.s.
	(0.040)	(0.063)	(0.076)	(0.098)		(0.052)	(0.062)	(0.071)		(0.050)	(0.063)	(0.060)	
% Town	0.024	0.116*	0.140*	0.002	n.s.	0.007	0.007	-0.014	n.s.	0.020	-0.017	0.068	n.s.
	(0.037)	(0.055)	(0.066)	(0.089)		(0.044)	(0.053)	(0.059)		(0.046)	(0.057)	(0.054)	
% Suburb	0.034	0.023	0.022	-0.025	n.s.	0.043	0.035	0.059	n.s.	0.044	0.044	0.064	n.s.
	(0.033)	(0.039)	(0.047)	(0.059)		(0.037)	(0.045)	(0.046)		(0.040)	(0.050)	(0.047)	
2020 Republican Vote	0.041	-0.026	-0.160	0.261	*	0.126	0.051	0.272	n.s.	0.123	0.154	0.259*	n.s.
Share	(0.080)	(0.133)	(0.162)	(0.208)		(0.103)	(0.124)	(0.140)		(0.096)	(0.120)	(0.120)	
% Age 65+	0.101	0.783*	0.590	0.417	n.s.	0.135	0.186	0.011	n.s.	0.100	-0.142	0.085	n.s.
	(0.201)	(0.362)	(0.432)	(0.593)		(0.267)	(0.322)	(0.375)		(0.242)	(0.304)	(0.307)	
% Age 5-18	-0.692*	-0.552	-0.315	-0.325	n.s.	-0.721	-0.240	-0.725	n.s.	-0.695*	-0.753	-0.721	n.s.
	(0.288)	(0.490)	(0.602)	(0.784)		(0.383)	(0.472)	(0.524)		(0.347)	(0.440)	(0.438)	
Change in Log Enrollment	-0.527***	-0.509**	-0.667***	-0.481*	n.s.	-0.732***	-0.790***	-0.686***	n.s.	-0.861***	-0.970***	-0.765***	n.s.
2019-22	(0.086)	(0.161)	(0.200)	(0.244)		(0.128)	(0.155)	(0.175)		(0.111)	(0.142)	(0.140)	
Change in % Racial	-0.334	-0.599	-0.451	-0.578	n.s.	-0.311	0.089	0.449	n.s.	0.113	-0.505	0.985*	*
Minority 2019-22	(0.342)	(0.553)	(0.686)	(0.834)		(0.438)	(0.533)	(0.592)		(0.403)	(0.520)	(0.497)	
Change in Free/Reduced	-0.012	-0.207	-0.150	-0.191	n.s.	0.024	-0.046	0.057	n.s.	-0.064	-0.061	-0.100	n.s.
2019-22	(0.099)	(0.176)	(0.220)	(0.251)		(0.152)	(0.188)	(0.198)		(0.144)	(0.185)	(0.175)	
Constant	-0.084***	-0.033**	-0.062***	0.005	**	-0.015	-0.037**	0.013	**	-0.076***	-0.160***	-0.102***	***
	(0.008)	(0.012)	(0.014)	(0.019)		(0.010)	(0.012)	(0.015)		(0.009)	(0.011)	(0.011)	
N	7510	1993	1993	1993		3532	3532	3532		5152	5152	5152	
R^2	0.078	0.148	0.075	0.036		0.100	0.056	0.089		0.075	0.048	0.032	

Note: All models are meta-regressions accounting for measurement error in the dependent variable.

Table 6. Direct and interaction effects of factors

	Math		Reading	
	Direct	Interaction with Not In-Person Schooling	Direct	Interaction with Not In-Person Schooling
Home Computer and Internet Access	0.319**	0.306	0.112	0.299
	(0.109)	(0.341)	(0.107)	(0.331)
Social Capital	0.013	-0.026	0.010	-0.020
	(0.018)	(0.052)	(0.017)	(0.051)
Trust in Institutions	0.060**	0.157*	0.008	0.164*
	(0.020)	(0.068)	(0.019)	(0.066)
School Resources	-0.027	-0.925	0.064	-0.492
	(0.270)	(0.896)	(0.257)	(0.848)
Pandemic Employment	0.221	-1.246*	0.031	-1.126*
	(0.169)	(0.491)	(0.163)	(0.471)
COVID-19 Death Rate	-0.178*	-0.481*	-0.124	-0.104
	(0.070)	(0.233)	(0.068)	(0.224)
COVID-19 Disruptions to Normal Life	-0.060***	0.015	-0.042**	0.033
	(0.016)	(0.044)	(0.016)	(0.042)
Anxiety and Depression	-0.020	-0.089*	-0.016	-0.038
	(0.011)	(0.039)	(0.011)	(0.038)

Note: All models are meta-regressions accounting for measurement error in the dependent variable. Each covariate and its interaction with not in-person schooling is included in a separate model, along with the covariates from column M6 (or R6) of Table 4 and state fixed effects. N=7,729 for math models and 7,510 for reading models.

Table 7. Effect of factors on key model coefficients

	Math		Reading	
	Base Model	All Factors	Base Model	All Factors
Free/Reduced Lunch	-0.251***	-0.175*	-0.329***	-0.307***
	(0.065)	(0.073)	(0.062)	(0.071)
% Racial Minority	-0.157*	-0.134	0.065	0.091
	(0.069)	(0.073)	(0.067)	(0.071)
% Remote Schooling	-0.272***	-0.221***	-0.112*	-0.082
	(0.056)	(0.057)	(0.054)	(0.055)
% Hybrid Schooling	-0.116***	-0.097**	-0.103**	-0.091**
	(0.035)	(0.035)	(0.033)	(0.034)
% Racial Minority ×	-0.485***	-0.502**	-0.263*	-0.258
% Not In-Person School	(0.137)	(0.170)	(0.130)	(0.163)

Note: All models are meta-regressions accounting for measurement error in the dependent variable. N=7,729 for math models and 7,510 for reading models. The "base model" is column M6 (or R6) of Table 4. The "All Factors" column includes the "base model" covariates and all listed direct and interaction effects in Table 6.

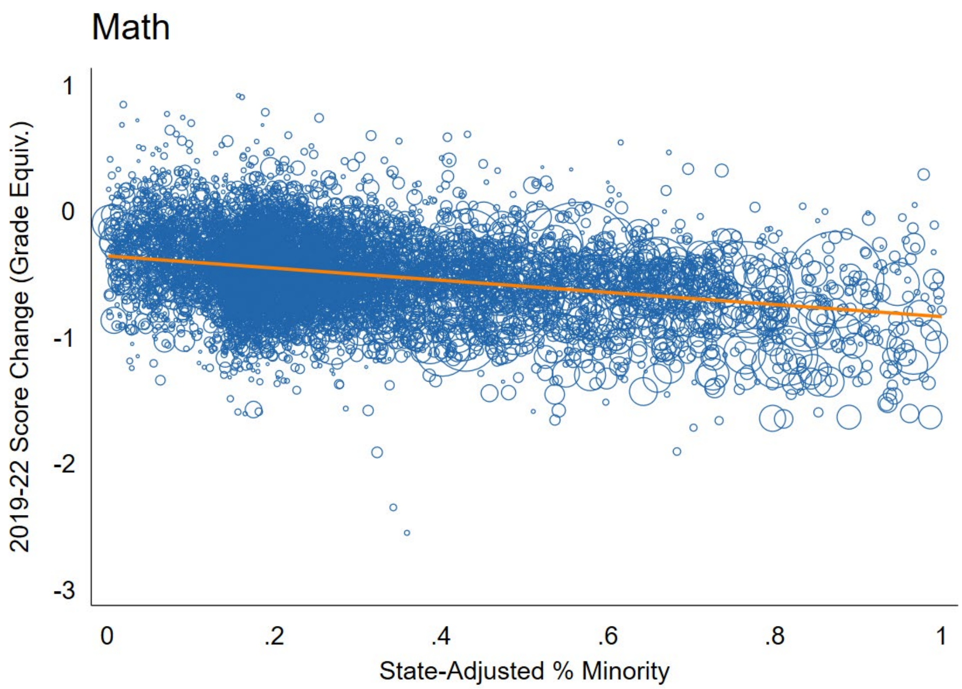
Figures

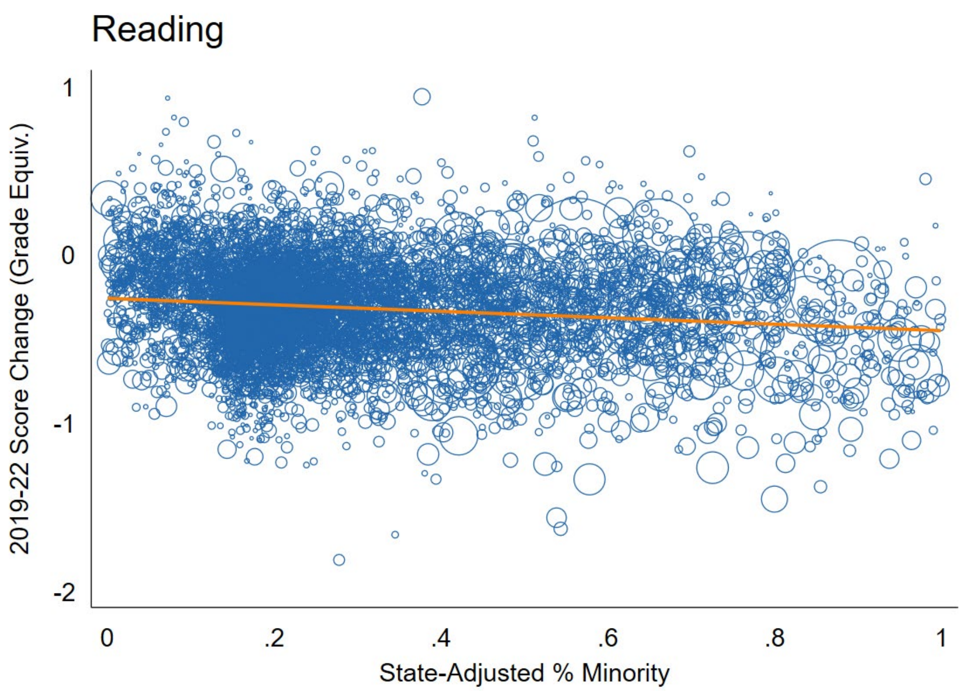
Figure 1. Bivariate correlations with 16-19, 19-22, and the differential change, math

Figure 2. 2019-22 score changes vs. district free/reduced price lunch rates

Note: We adjust free/reduced lunch by state by regressing free/reduced lunch on state fixed effects, then adding the constant from that regression (set at the level of an average state) to each district's residual.

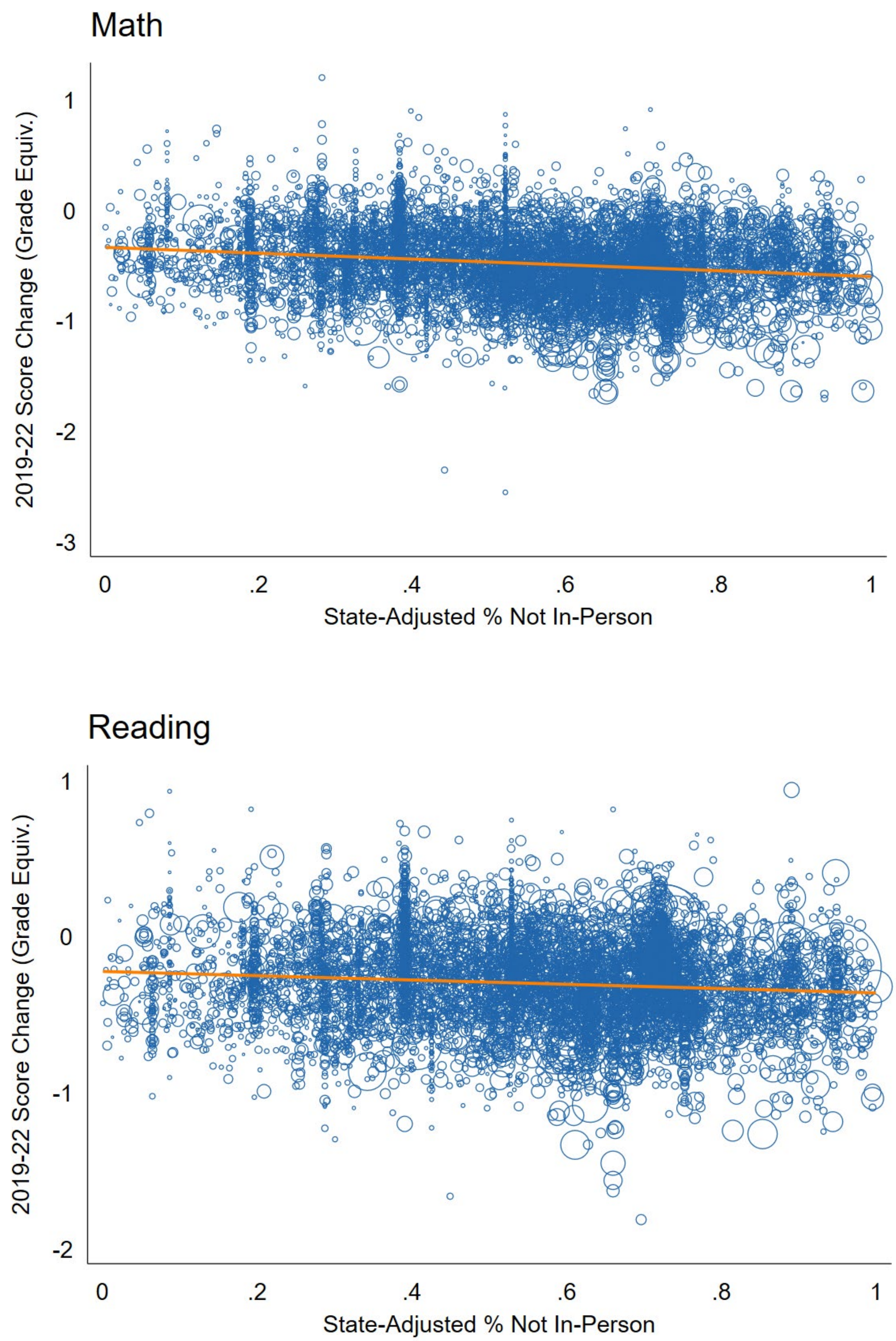
Figure 3. 2019-22 Score changes vs. share of minority students in district





Note: We adjust percent minority by state by regressing percent minority on state fixed effects, then adding the constant from that regression (set at the level of an average state) to each district's residual.

Figure 4. 2019-22 Score changes vs. amount of time not in in-person schooling



Note: We adjust percent not in-person by state by regressing percent not in-person on state fixed effects, then adding the constant from that regression (set at the level of an average state) to each district's residual.

Figure 5. Math achievement losses vs percent not-in-person, by percent minority

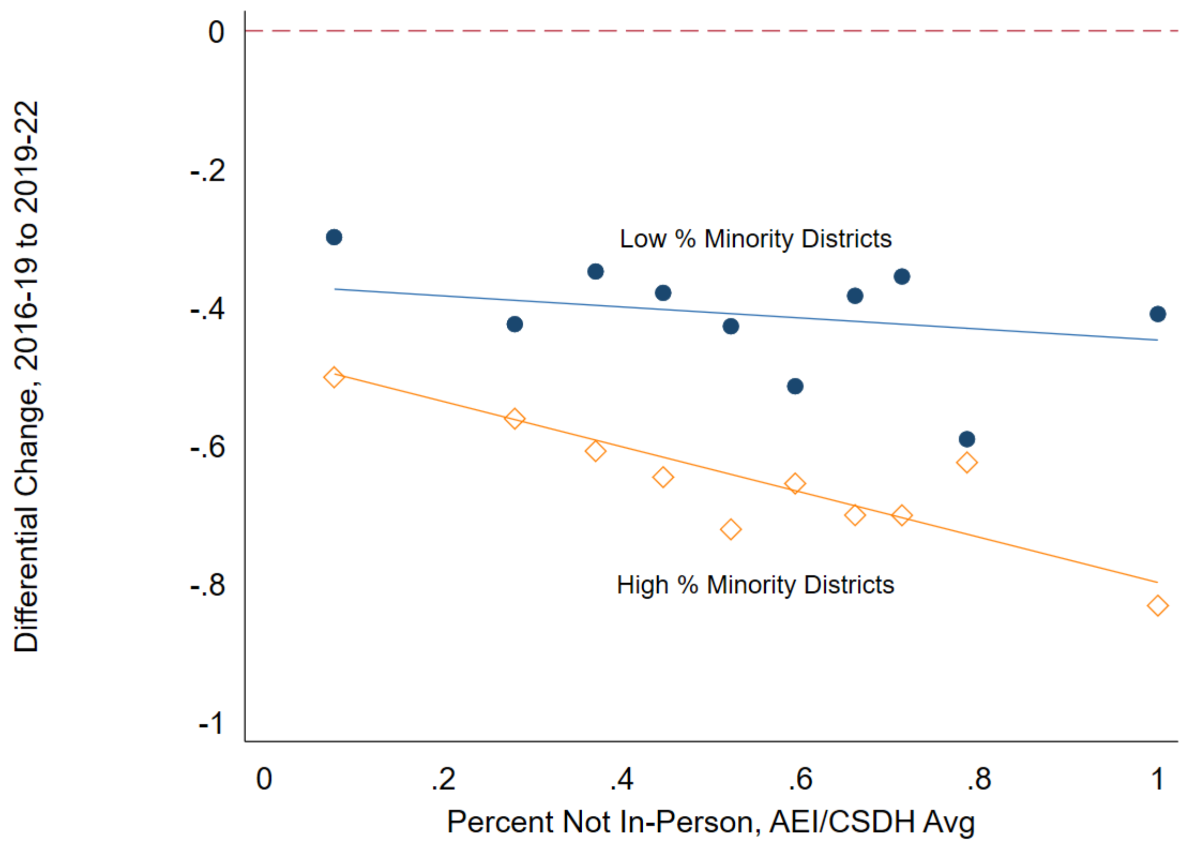


Figure 6. Comparison of achievement changes between subgroups within districts, math

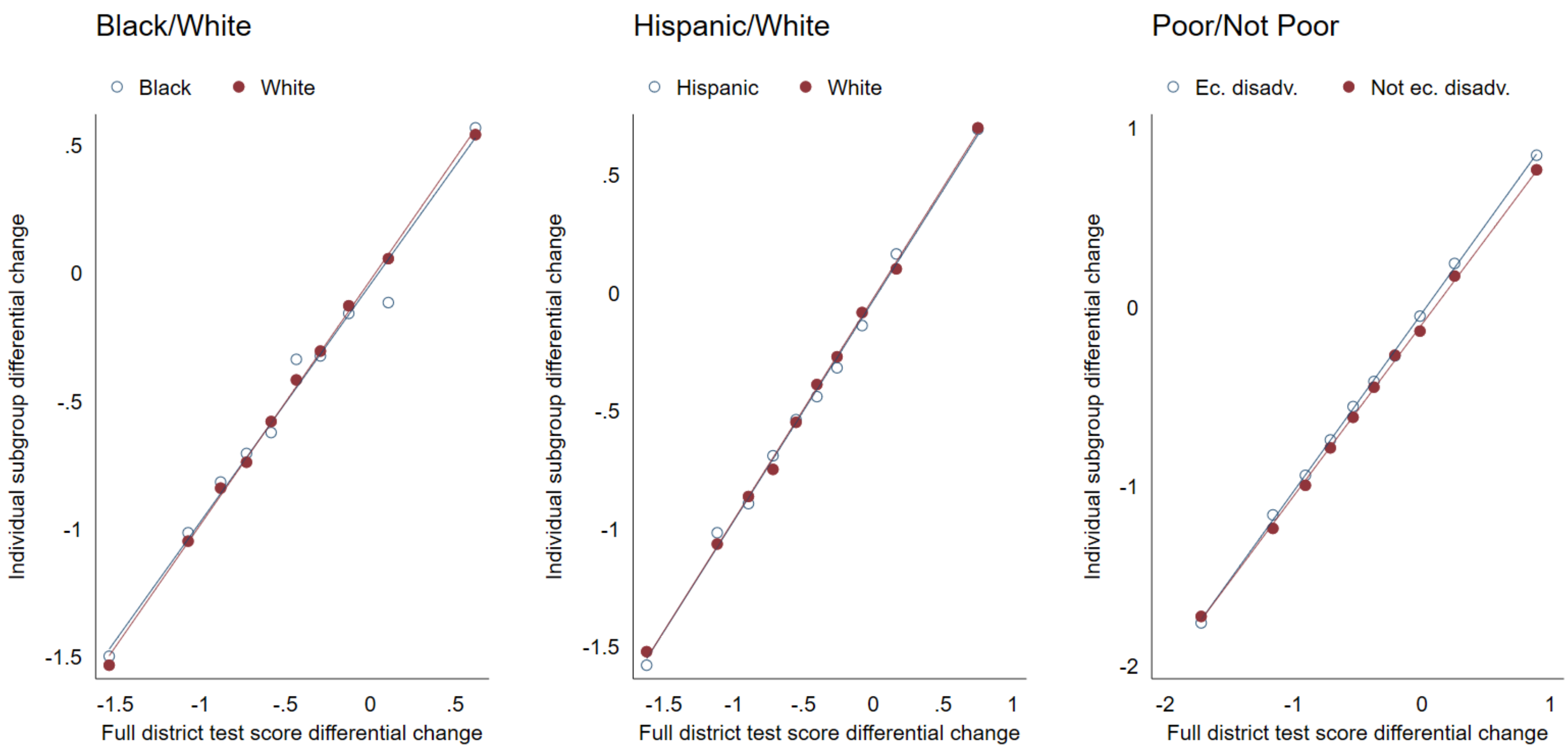


Figure 7. Distribution of predicted 3-year changes in test scores pre- and post-pandemic

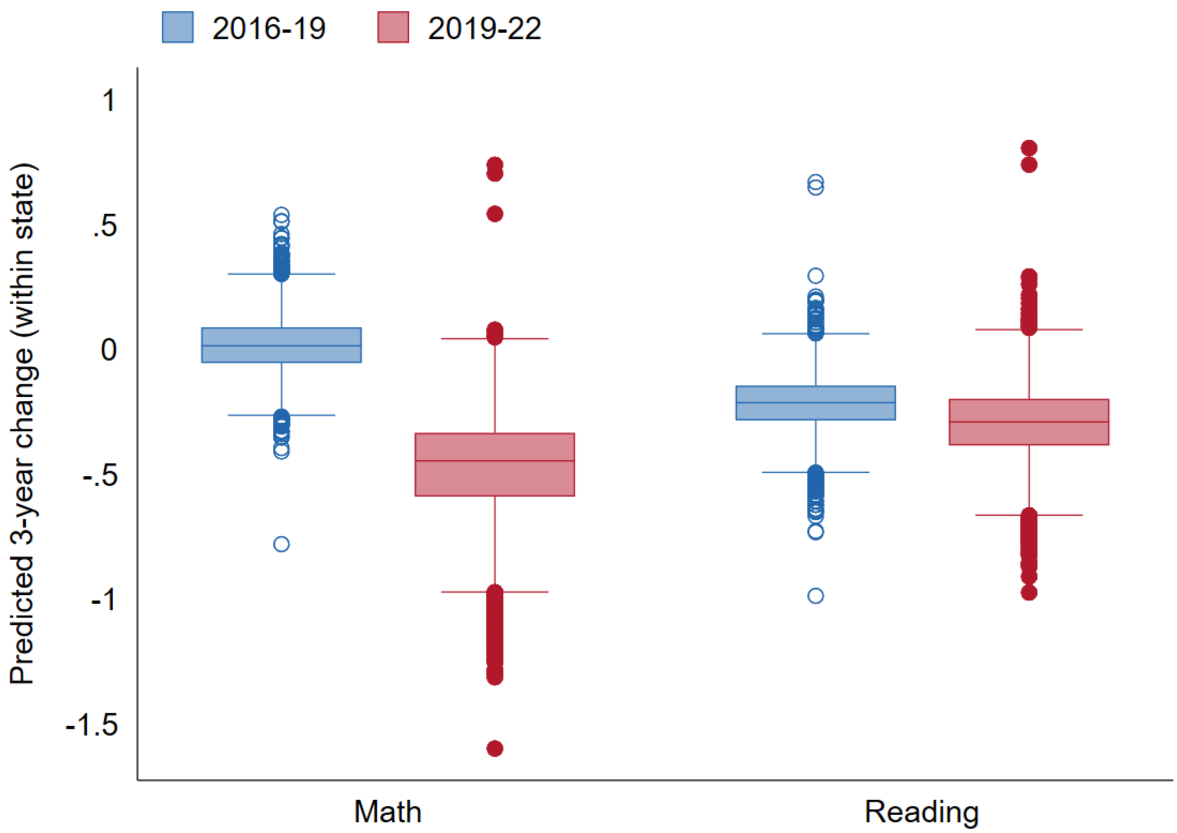


Figure 8. Variance of predicted 3-year changes in test scores pre- and post-pandemic

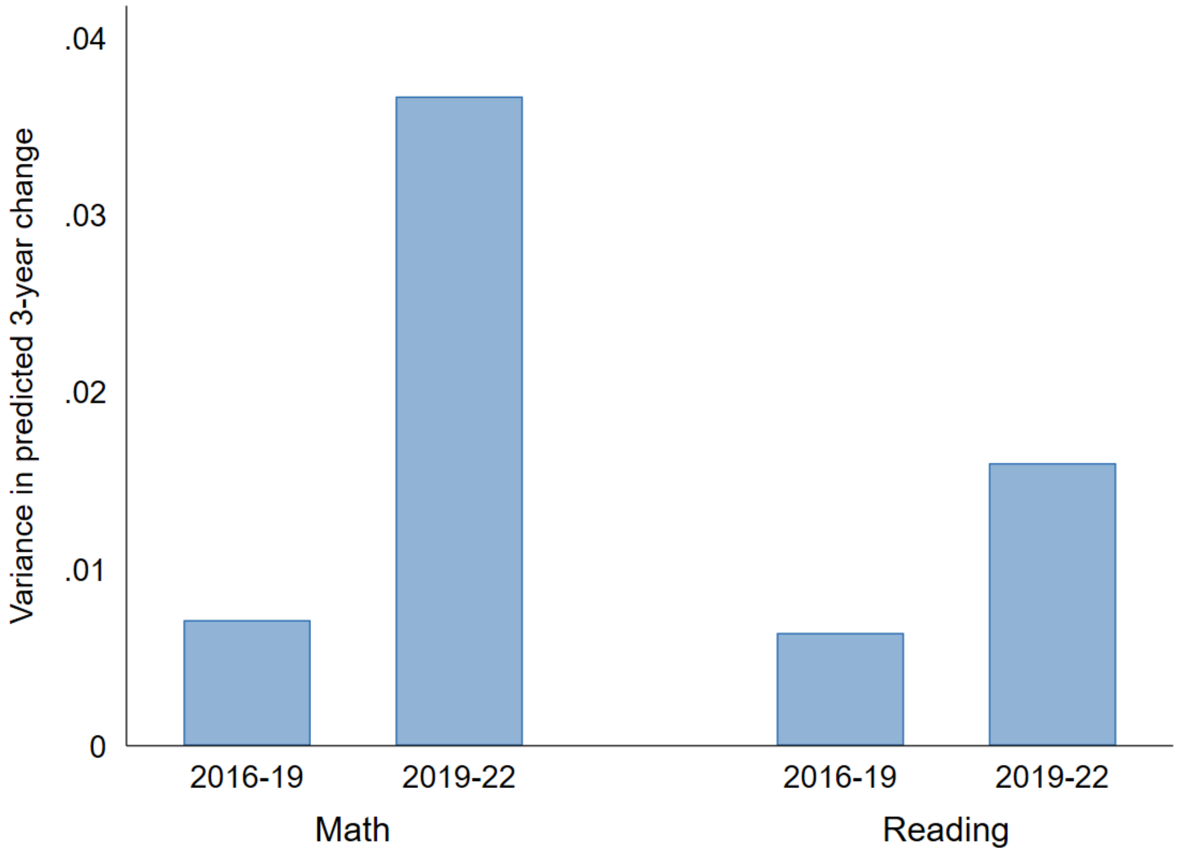
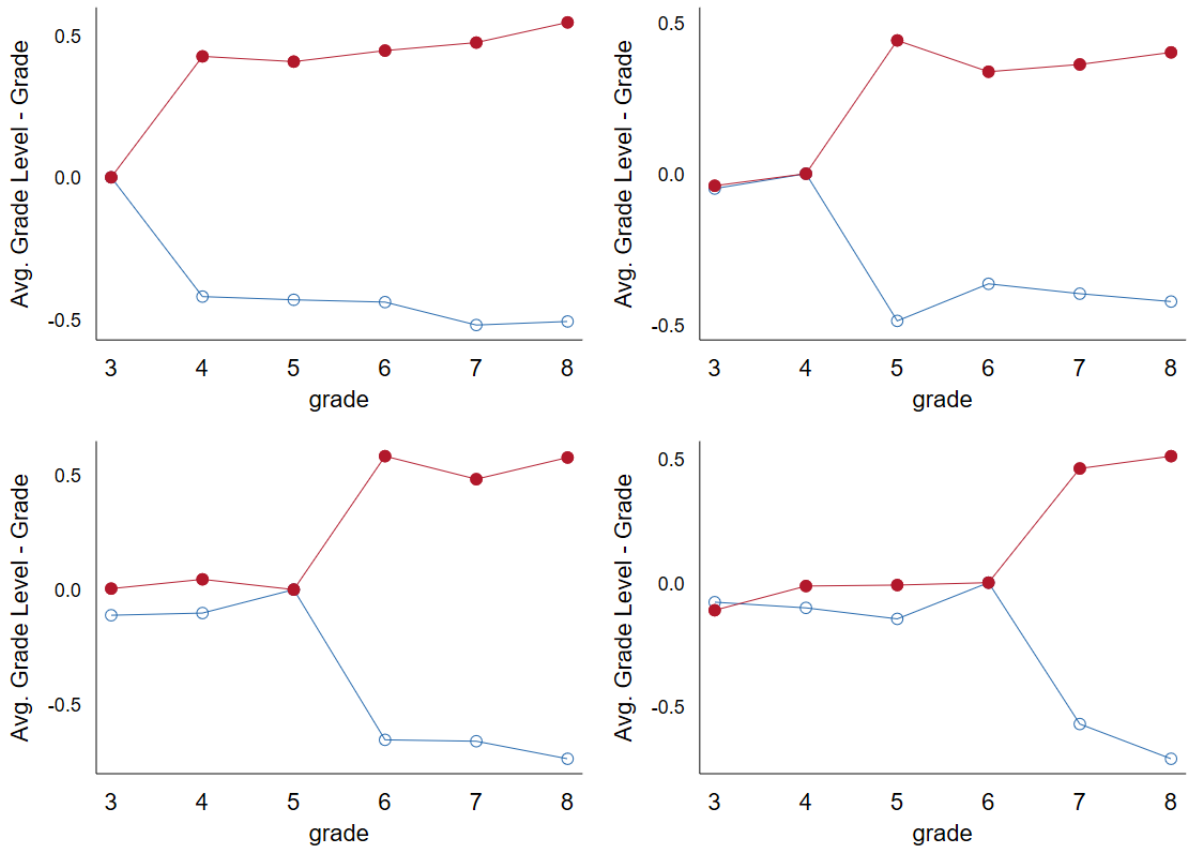


Figure 9. Persistence of large changes in cohort math achievement in later grades



Note: In each panel, cohorts are sorted into deciles based on their district's average improvement from one grade to the next, starting with grades 3-4. The top and bottom decile are shown here. Scores are adjusted to equal 0 in the grade before the shock.

Appendix A: Additional Tables and Figures

Table A1. Subgroup achievement descriptive statistics

	Math			Reading		
Subgroup	Mean	Overall SD	Within-State SD	Mean	Overall SD	Within-State SD
White-Black Sample						
White	-0.484	0.179	0.048	-0.085	0.277	0.193
Black	-0.519	0.377	0.272	-0.011	0.428	0.251
White-Hispanic Sample						
White	-0.481	0.214	0.098	-0.075	0.345	0.261
Hispanic	-0.531	0.354	0.269	-0.032	0.418	0.263
Poor-Not Poor Sample						
Poor	-0.517	0.396	0.310	-0.131	0.459	0.362
Not Poor	-0.543	0.420	0.339	-0.177	0.450	0.389

Table A2. Subgroup covariate descriptive statistics

	White-Black Sample			White-Hispanic Sample			Poor-Not Poor Sample		
Variable	Mean	Overall SD	Within-State SD	Mean	Overall SD	Within-State SD	Mean	Overall SD	Within-State SD
% Free/Reduced Lunch	0.523	0.226	0.206	0.482	0.221	0.195	0.481	0.205	0.180
% Minority	0.396	0.248	0.213	0.350	0.250	0.214	0.272	0.269	0.211
% in Urban School	0.180	0.345	0.327	0.113	0.286	0.281	0.068	0.227	0.222
% in Rural School	0.208	0.306	0.255	0.289	0.377	0.338	0.438	0.441	0.415
% in Suburban School	0.460	0.446	0.371	0.381	0.446	0.372	0.295	0.426	0.377
% in Town School	0.152	0.307	0.288	0.217	0.367	0.351	0.200	0.359	0.354
% Age 65+	0.158	0.044	0.041	0.168	0.051	0.050	0.176	0.051	0.050
% Age 5-18	0.170	0.030	0.028	0.172	0.033	0.032	0.170	0.033	0.032
2020 Republican Vote Share	0.532	0.181	0.132	0.571	0.186	0.139	0.605	0.185	0.144
Log 3-8 Enrl. Chg.	-0.047	0.081	0.079	-0.045	0.087	0.085	-0.050	0.089	0.088
% FRL Chg.	-0.027	0.085	0.068	-0.035	0.085	0.068	-0.026	0.079	0.067
% Minority Chg.	0.017	0.023	0.022	0.016	0.026	0.025	0.012	0.025	0.025
% Remote (R2L/CSDH Avg.)	0.215	0.260	0.176	0.196	0.252	0.183	0.162	0.235	0.173
% Hybrid (R2L/CSDH Avg.)	0.420	0.290	0.225	0.392	0.289	0.215	0.362	0.287	0.228
% In-person (R2L/CSDH Avg.)	0.365	0.350	0.223	0.412	0.365	0.230	0.477	0.364	0.255

Table A3. CTIS variables

Variable	Category	Time period(s) used	Description	Source variable name (CTIS instrument question)	Start date of CTIS collection	End date of CTIS collection	Changes in wording	CTIS questionnaire original wording	CTIS questionnaire final wording
% of CTIS respondents with a child in hybrid schooling, among those with a child in their household	Remote/ hybrid schooling	Period 1	E2: Proportion of people (among those who reported having a child at home) answering "Going to in-person classes part-time"; P5: Proportion answering "Mix of in-person and online, remote, or distance learning"	E2_2, P5	11/24/20	6/15/22	12/19/21	Do any of the following apply to any children in your household (pre-K–grade 12)? Going to in-person classes part-time (2)	Thinking about your oldest child under age 18, which of the following best describes their current schooling?
% of CTIS respondents with a child in online schooling, among those with a child in their household	Remote/ hybrid schooling	Period 1	E2: Proportion of people (among those who reported having a child at home) answering NO to both "Going to in-person classes full-time" AND "Going to in-person classes part-time"; P5: Proportion of people answering "Online, remote, or distance learning"	E2_1 + E2_2, P5	11/24/20	6/15/22	12/19/21	Do any of the following apply to any children in your household (pre-K–grade 12)?	Thinking about your oldest child under age 18, which of the following best describes their current schooling?
% of CTIS respondents reporting an anxiety score >=3, among those with a child in their household	Mental health	Period 1, Period 2	Proportion of responses with score 3 or 4, where score 4 = all the time, 3 = most of the time, 2 = some of the time, 1= none of the time	C8_1, C8a_1	4/4/20	6/15/22		In the past 5 days, how often have you ...	In the past 7 days, how often have you ...
% of CTIS respondents reporting a depression score >=3, among those with a child in their household	Mental health	Period 1, Period 2	Proportion of responses with score 3 or 4, where score 4 = all the time, 3 = most of the time, 2 = some of the time, 1= none of the time	C8_2, C8a_2	4/4/20	6/15/22		In the past 5 days, how often have you ...	In the past 7 days, how often have you ...
% of CTIS respondents who did not work for pay in last month, among those with a child in the household	Work	Combined	Proportion of "no" responses	D9	9/12/20	6/15/22		In the past 4 weeks, did you do any kind of work for pay?	
% of CTIS respondents vaccinated, among those with a child in the	COVID precautions	Period 1, Period 2	Proportion of "yes" responses	V1	1/6/21	6/15/22		Have you had a COVID-19 vaccination?	

household									
% of CTIS respondents who usually wore a mask, among those with a child in the household	COVID precautions	Period 1, Period 2	Proportion of “all/most/some of the time” responses	C14, C14a	9/12/20	6/15/22	5/20/21	In the past 7 days, how often did you wear a mask when in public?	In the past 5 days, how often did you wear a mask when in public?
% of CTIS respondents "worried about COVID," among those with a child in the household	COVID precautions	Period 1, Period 2	Proportion of responses coded as 1 or 2, where 1 = very worried, 2 = somewhat worried, 3 = not too worried, 4=not worried at all	C9	4/4/20	5/20/21		How worried do you feel that you or someone in your immediate family might become seriously ill from COVID-19 (coronavirus disease)?	
% of CTIS respondents who went to market/grocery/pharmacy in last 24 hours, among those with a child in the household	"Normal life" during pandemic	Period 1, Period 2	Proportion of “yes” responses, to having gone to an indoors grocery store/market outside their home in the last 24 hours	C13	9/12/20	6/15/22		In the past 24 hours, have you done any of the following? Please select all that apply.	
% of CTIS respondents who visited a bar/restaurant/café in last 24 hours, among those with a child in the household	"Normal life" during pandemic	Period 1, Period 2	Proportion of “yes” responses, to having gone to an indoors bar/cafe/restaurant in the last 24 hours	C13	9/12/20	6/15/22		In the past 24 hours, have you done any of the following? Please select all that apply.	
% of CTIS respondents who saw an external person in last 24 hours, among those with a child in the household	"Normal life" during pandemic	Period 1, Period 2	Proportion of “yes” responses, to having met indoors with another person not from their household in the last 24 hours	C13	9/12/20	6/15/22		In the past 24 hours, have you done any of the following? Please select all that apply.	
% of CTIS respondents who attended a large event in last 24 hours, among those with a child in the household	"Normal life" during pandemic	Period 1, Period 2	Proportion of “yes” responses, to having attended an indoors event with more than 10 people in the last 24 hours	C13	9/12/20	6/15/22		In the past 24 hours, have you done any of the following? Please select all that apply.	
% of CTIS respondents who "always" avoid socializing, among those with a child in the household	"Normal life" during pandemic	Period s1, Period 2	Proportion of people answering “always”	C7, C7a	4/4/20	6/15/22	5/20/21	To what extent are you intentionally avoiding contact with other people?	In the past 7 days, how often did you intentionally avoid contact with other people?

Table A4. Factor scoring coefficients

Category	Variables	Coefficient
Home Computer and Internet Access	% of under-18 residents with access to a computer and broadband internet, 2015-19 5-yr ACS	N/A
School Resources	District staff per student, 2018-19 CCD	N/A
Social Capital	County-level community health subindex of Joint Economic Committee	0.342
	Clustering, Opportunity Insights data	0.281
	Support, Opportunity Insights data	0.229
	Civic organizations in county, Opportunity Insights data	0.245
	Volunteering rate of county, Opportunity Insights data	0.109
Trust in Institutions	County-level institutional trust subindex of Joint Economic Committee	N/A
Pandemic Employment	% of CTIS respondents who worked for pay in last month if child in HH, both years combined	N/A
COVID-19 Death Rate	Average daily COVID deaths/100k in both years, USAFacts	N/A
COVID-19 Disruptions to Normal Life	% change in restaurant visits from pre-pandemic to pandemic, Safegraph	-0.011
	% change in retail/recreation activity from pre-pandemic to pandemic, Google GPS data	-0.038
	% change in grocery/pharmacy activity from pre-pandemic to pandemic, Google GPS data	-0.030
	CTIS respondents who went to market/grocery/pharmacy in last 24 hours if child in HH, year 1	-0.040
	CTIS respondents who went to market/grocery/pharmacy in last 24 hours if child in HH, year 2	-0.042
	CTIS respondents who visited a bar/restaurant/café in last 24 hours if child in HH, year 1	-0.080
	CTIS respondents who visited a bar/restaurant/café in last 24 hours if child in HH, year 2	-0.057
	CTIS respondents who saw an external person in last 24 hours if child in HH, year 1	-0.105
	CTIS respondents who saw an external person in last 24 hours if child in HH, year 2	-0.099
	CTIS respondents who attended a large event in last 24 hours if child in HH, year 1	-0.100
	CTIS respondents who attended a large event in last 24 hours if child in HH, year 2	-0.047
	CTIS respondents who "always" avoid socializing if child in HH, year 1	0.051
	CTIS respondents who "always" avoid socializing if child in HH, year 2	0.024
	CTIS respondents who usually wore a mask if child in HH, year 1	0.077
	CTIS respondents who usually wore a mask if child in HH, year 2	0.120
	CTIS respondents "worried about COVID" score if child in HH, year 1	0.055
	CTIS respondents "worried about COVID" score if child in HH, year 2	0.091
	CTIS respondents vaccinated if child in HH, year 1	0.018
	CTIS respondents vaccinated if child in HH, year 2	0.102
Anxiety and Depression	CTIS respondents in "anxious" bin if child in HH, year 1	0.419
	CTIS respondents in "anxious" bin if child in HH, year 2	0.178
	CTIS respondents in "depressed" bin if child in HH, year 1	0.403
	CTIS respondents in "depressed" bin if child in HH, year 2	0.171

Table A5. Preferred specifications, 2019-22 change outcome

	Math			Reading		
Free/Reduced Lunch	-0.227***	-0.364***	-0.397***	-0.329***	-0.398***	-0.432***
	(0.036)	(0.042)	(0.043)	(0.034)	(0.041)	(0.041)
% Racial Minority	-0.319***	-0.136**	-0.118**	-0.037	0.050	0.064
	(0.036)	(0.046)	(0.045)	(0.034)	(0.044)	(0.044)
% Remote Schooling	-0.424***	-0.315***	-0.330***	-0.256***	-0.201***	-0.206***
	(0.035)	(0.038)	(0.037)	(0.033)	(0.036)	(0.035)
% Hybrid Schooling	-0.226***	-0.188***	-0.185***	-0.180***	-0.157***	-0.152***
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
% Racial Minority ×	-0.317***	-0.331***	-0.380***	-0.173*	-0.184*	-0.221**
% Not In-Person School	(0.091)	(0.092)	(0.091)	(0.086)	(0.087)	(0.086)
Log Enrollment		-0.020**	-0.017**		-0.011	-0.008
		(0.007)	(0.006)		(0.006)	(0.006)
% Rural		0.064*	0.054		0.055*	0.046
		(0.029)	(0.028)		(0.027)	(0.027)
% Town		0.031	0.021		0.027	0.019
		(0.027)	(0.026)		(0.025)	(0.025)
% Suburb		0.017	0.032		0.013	0.025
		(0.024)	(0.023)		(0.022)	(0.022)
2020 Republican Vote		0.160**	0.239***		0.056	0.123*
Share		(0.056)	(0.055)		(0.053)	(0.053)
% Age 65+		0.340*	0.149		0.052	-0.083
		(0.137)	(0.136)		(0.132)	(0.131)
% Age 5-18		0.452*	0.331		0.216	0.104
		(0.199)	(0.196)		(0.190)	(0.189)
Change in Log Enrollment			-0.504***			-0.315***
2019-22			(0.058)			(0.057)
Change in % Racial			-2.597***			-2.241***
Minority 2019-22			(0.228)			(0.222)
Change in Free/Reduced			0.028			-0.103
2019-22			(0.066)			(0.065)
State Fixed Effects?	X	X	X	X	X	X
N	7729	7729	7729	7510	7510	7510
R^2	0.332	0.353	0.417	0.158	0.163	0.214

Note: All models are meta-regressions accounting for measurement error in the dependent variable.

Table A6. Preferred specifications, adjusted CTIS schooling modality variables

	Math			Reading		
Free/Reduced Lunch	-0.139**	-0.200**	-0.240***	-0.229***	-0.266***	-0.316***
	(0.053)	(0.064)	(0.064)	(0.050)	(0.061)	(0.062)
% Racial Minority	-0.276***	-0.183**	-0.155*	-0.015	0.048	0.070
	(0.054)	(0.069)	(0.069)	(0.052)	(0.067)	(0.066)
% Remote Schooling	-0.532***	-0.525***	-0.565***	-0.295***	-0.314***	-0.349***
	(0.074)	(0.082)	(0.082)	(0.071)	(0.078)	(0.078)
% Hybrid Schooling	-0.281**	-0.279**	-0.273**	-0.332***	-0.333***	-0.345***
	(0.098)	(0.098)	(0.098)	(0.093)	(0.094)	(0.094)
% Racial Minority ×	-0.316*	-0.380**	-0.427**	-0.142	-0.182	-0.208
% Not In-Person School	(0.136)	(0.137)	(0.136)	(0.129)	(0.130)	(0.130)
Log Enrollment		0.000	0.001		0.006	0.006
		(0.010)	(0.010)		(0.009)	(0.009)
% Rural		0.073	0.074		0.078	0.082*
		(0.043)	(0.042)		(0.040)	(0.040)
% Town		0.018	0.013		0.023	0.023
		(0.039)	(0.039)		(0.037)	(0.037)
% Suburb		0.006	0.020		0.027	0.034
		(0.035)	(0.035)		(0.033)	(0.032)
2020 Republican Vote		-0.086	-0.023		-0.061	-0.030
Share		(0.085)	(0.085)		(0.081)	(0.081)
% Age 65+		0.510*	0.330		0.226	0.122
		(0.208)	(0.208)		(0.201)	(0.201)
% Age 5-18		-0.280	-0.356		-0.614*	-0.655*
		(0.300)	(0.299)		(0.289)	(0.288)
Change in Log Enrollment			-0.722***			-0.545***
2019-22			(0.088)			(0.086)
Change in % Racial			-1.403***			-0.305
Minority 2019-22			(0.350)			(0.342)
Change in Free/Reduced			0.209*			-0.010
2019-22			(0.100)			(0.099)
State Fixed Effects?	X	X	X	X	X	X
N	7729	7729	7729	7510	7510	7510
R^2	0.281	0.290	0.366	0.059	0.064	0.088

Note: All models are meta-regressions accounting for measurement error in the dependent variable.

Table A7. Direct and interaction effects of factors, 2019-22 change

	Math		Reading	
	Direct	Interaction with Not In-Person Schooling	Direct	Interaction with Not In-Person Schooling
Home Computer and Internet Access	0.062	0.069	-0.102	-0.012
	(0.072)	(0.226)	(0.070)	(0.218)
Social Capital	0.007	-0.080*	0.005	-0.051
	(0.012)	(0.034)	(0.011)	(0.034)
Trust in Institutions	-0.001	0.039	-0.037**	0.045
	(0.013)	(0.045)	(0.012)	(0.044)
School Resources	-0.045	0.310	0.133	0.167
	(0.177)	(0.589)	(0.168)	(0.557)
Pandemic Employment	0.283*	-0.969**	0.187	-0.759*
	(0.112)	(0.325)	(0.107)	(0.311)
COVID-19 Death Rate	0.107*	-0.330*	0.061	-0.067
	(0.046)	(0.155)	(0.045)	(0.149)
COVID-19 Disruptions to Normal Life	-0.038***	0.029	-0.011	0.038
	(0.011)	(0.029)	(0.010)	(0.028)
Anxiety and Depression	-0.024**	-0.034	-0.018*	0.013
	(0.008)	(0.026)	(0.007)	(0.025)

Note: All models are meta-regressions accounting for measurement error in the dependent variable.

Table A8. Effect of factors on key model coefficients, 2019-22 change

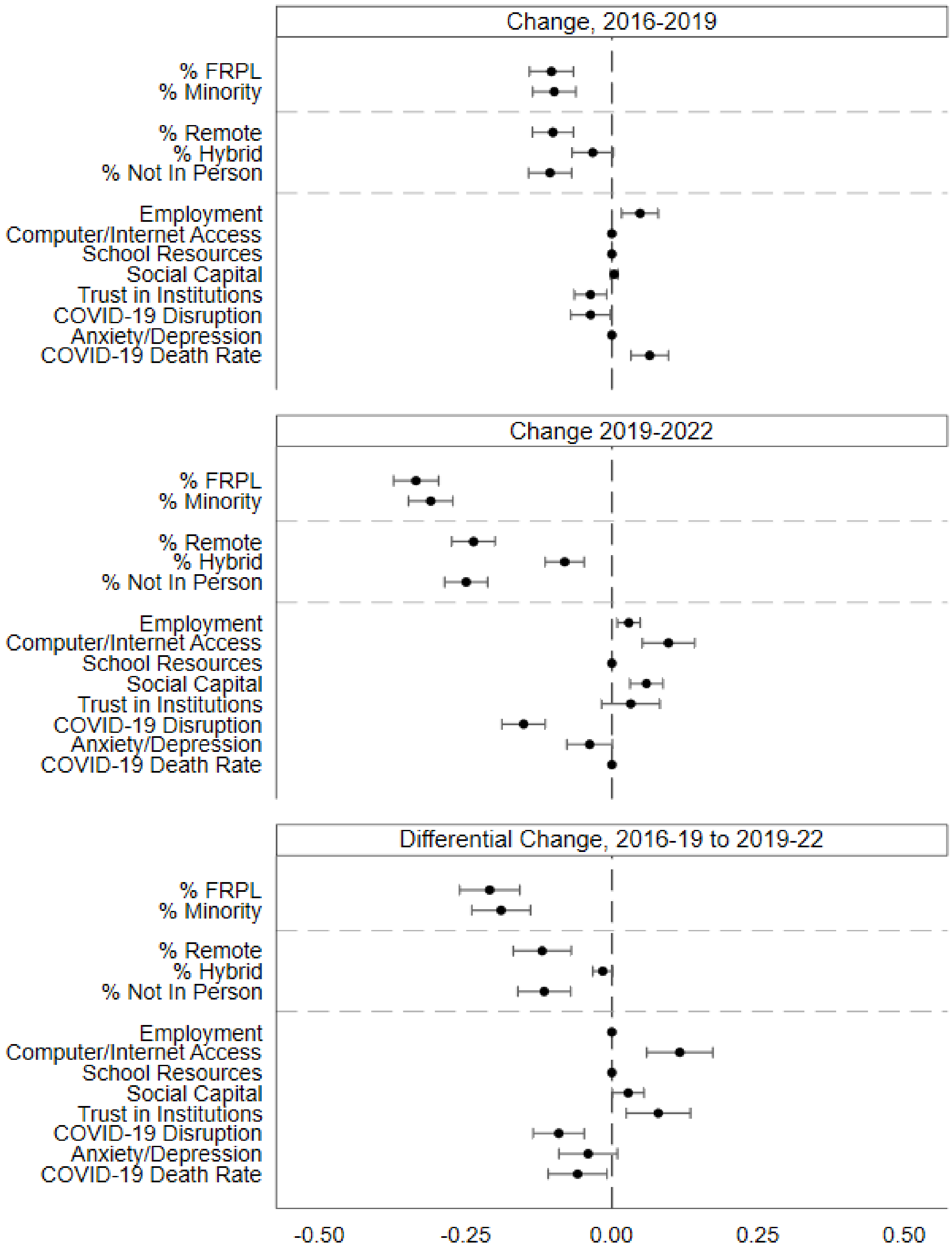
	Math		Reading	
	Base Model	All Factors	Base Model	All Factors
Free/Reduced Lunch	-0.397***	-0.398***	-0.432***	-0.460***
	(0.043)	(0.048)	(0.041)	(0.046)
% Racial Minority	-0.118**	-0.140**	0.064	0.036
	(0.045)	(0.048)	(0.044)	(0.047)
% Remote Schooling	-0.330***	-0.318***	-0.206***	-0.209***
	(0.037)	(0.038)	(0.035)	(0.036)
% Hybrid Schooling	-0.185***	-0.170***	-0.152***	-0.148***
	(0.023)	(0.023)	(0.022)	(0.022)
% Racial Minority ×	-0.380***	-0.439***	-0.221**	-0.248*
% Not In-Person School	(0.091)	(0.113)	(0.086)	(0.108)

Note: All models are meta-regressions accounting for measurement error in the dependent variable. N=7,729 for math models and 7,510 for reading models. The "base model" is column M6 (or R6) of Table 4. The "All Factors" column includes the "base model" covariates and all listed direct and interaction effects in Table A7.

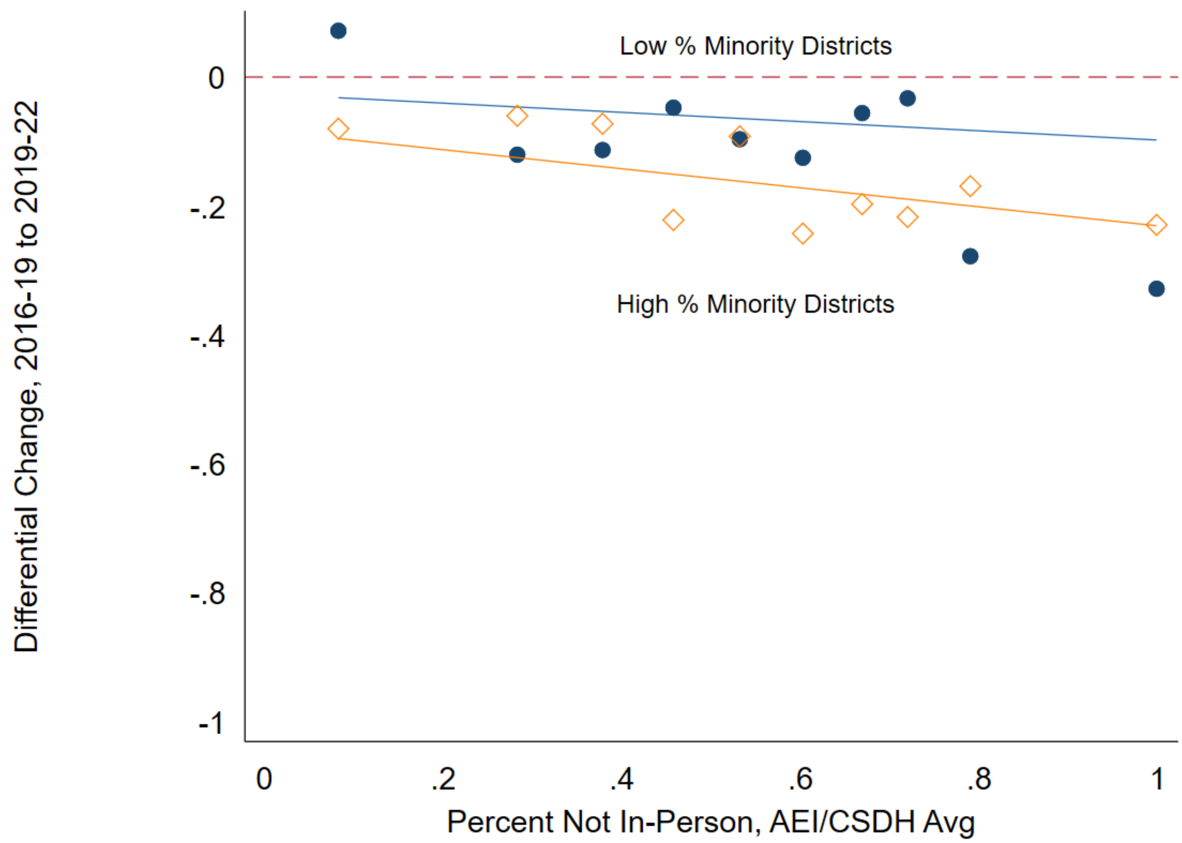
Table A9. Correlations of 2020-21 remote and hybrid learning source data

	Overall			Within-State		
	R2L	CSDH	CTIS	R2L	CSDH	CTIS
Remote						
R2L	1.000			1.000		
CSDH	0.804	1.000		0.679	1.000	
CTIS	0.678	0.690	1.000	0.451	0.515	1.000
Hybrid						
R2L	1.000			1.000		
CSDH	0.518	1.000		0.404	1.000	
CTIS	0.403	0.449	1.000	0.231	0.245	1.000

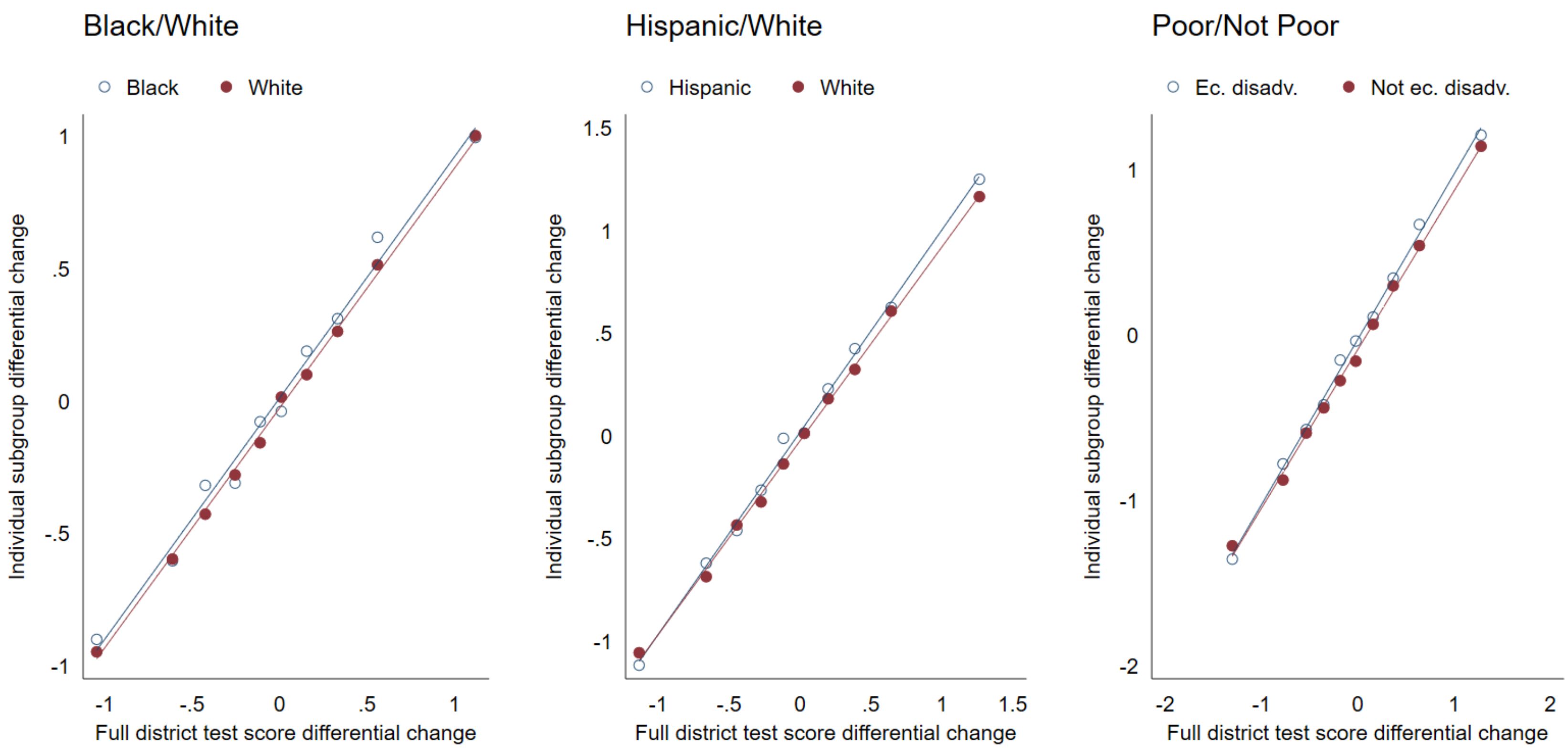
Appendix Figure A1. Bivariate correlations with 16-19, 19-22, and the difference, reading



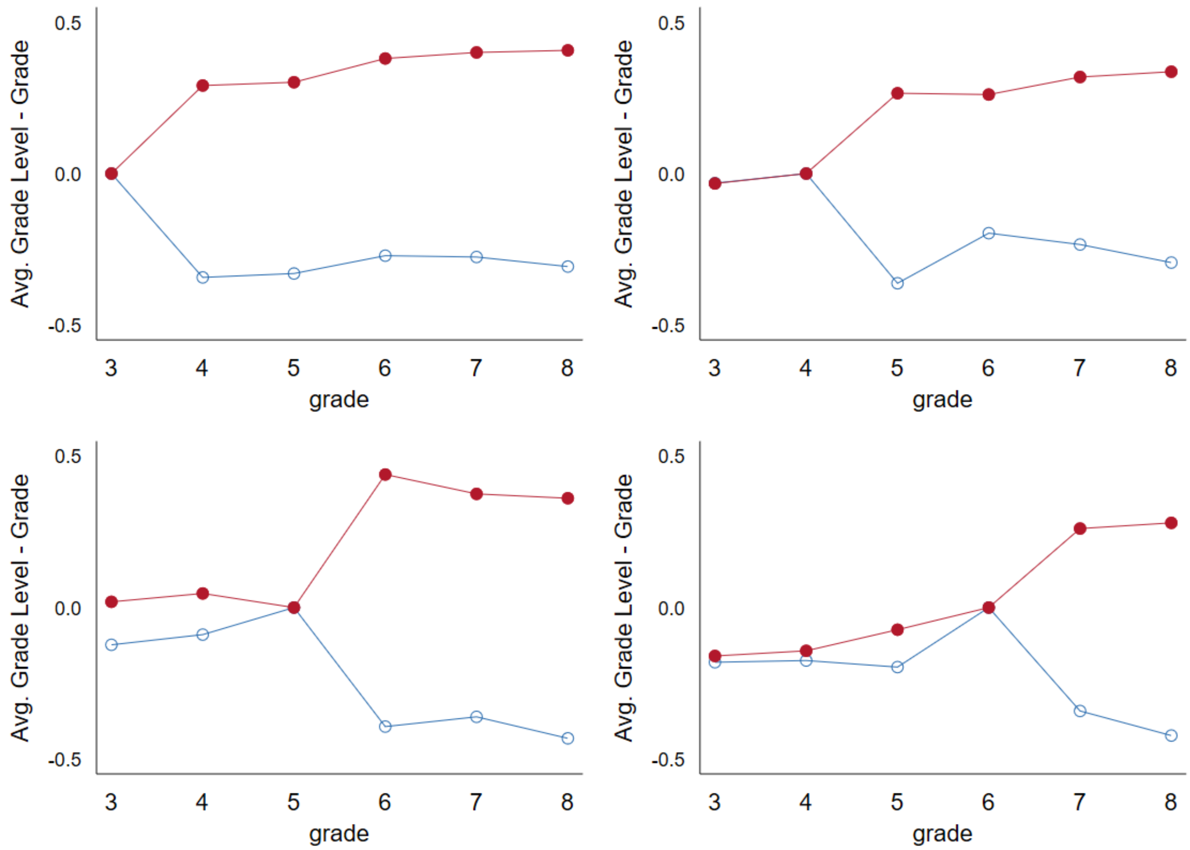
Appendix Figure A2. RLA achievement losses vs percent not-in-person, by percent minority



Appendix Figure A3. Comparison of achievement changes between subgroups within districts, reading



Appendix Figure 4: Persistence of large changes in cohort RLA achievement in later grades, 2009-2019



Note: In each panel, cohorts are sorted into deciles based on their district's average improvement from one grade to the next, starting with grades 3-4. The top and bottom decile are shown here. Scores are adjusted to equal 0 in the grade before the shock.