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RACIAL DIFFERENCES IN PARENT RESPONSE TO COVID SCHOOLING POLICIES

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ABSTRACT

This paper examines whether school COVID-19 policies influenced enrollment differently by student age and race/ethnicity. Unlike much prior research, we (i) analyze enrollments for virtually the entire U.S. public school population for both the 2020-21 and 2021-22 school years, (ii) compare enrollment trends within districts in order to isolate subgroup heterogeneity from district characteristics, and (iii) account for district selection into preferred learning modes. Analyzing data on over 9,000 districts that serve more than 90% of public school students in the U.S., we find enrollment responses to COVID policies differed notably. We find that White enrollments declined more than Black, Hispanic, and Asian enrollments in districts that started the 2020-21 school year virtually, but in districts that started in-person the reverse was true: non-White enrollments declined more than White enrollments. Moreover, Black, Hispanic, and Asian families responded more than White families to higher COVID-19 death rates in the months preceding the start of the 2021 school year. In 2021-22, enrollment differences by the previous year's learning mode persisted. Racial/ethnic differences did not vary by whether the district required masking in classrooms. These findings are consistent with the greater risk faced by communities of color during the pandemic and demonstrate an additional source of disparate impact from COVID policies.

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1 Introduction

The COVID-19 pandemic presented school administrators with unprecedented challenges as they sought to balance the twin goals of protecting the health of students and teachers while continuing to provide instruction to millions of children. Ultimately, thousands of districts opted to offer virtual or hybrid instruction during the 2020-21 school year and thousands required masks during the 2021-22 school year. Worried about health risks and dissatisfied with the available schooling options, many families pulled their young children from public schools. Indeed, the COVID-19 pandemic led to a 2.8% decline in public school enrollments in fall 2020, the largest single-year decline in US history (Malkus, 2022). Enrollments in 2021-22 remained below pre-pandemic levels in 73% of districts.

Prior research has explored how school enrollment changed in districts with different COVID policies. Most studies have found larger enrollment declines for younger children and in districts that only offered virtual learning in 2020-21 (Dee & Murphy, 2021; Malkus, 2022; Musaddiq et al., 2022). However, earlier work is limited to a sample of districts, does not thoroughly explore enrollment changes in 2021-22, and does not systematically study whether enrollment responses to school COVID policies differed across demographic groups.[1]

In this paper, we re-examine the relationship between COVID schooling policies and student enrollment, with a particular focus on differential responses by race and ethnicity. Given that prior research finds virtual instruction is associated with lower levels of student achievement (Jack et al., 2022), and the fact that enrollment directly determines school district funding, it is particularly important to understand how different racial groups responded to COVID policies. There are several reasons to suspect such differential responses. First, communities of color faced greater risks from COVID. Age-adjusted COVID-19 mortality rates in 2020 were consistently higher for racial and ethnic minorities than for White

[1] Malkus (2022) is the most comprehensive analysis of enrollment changes to date, but the author presents results as associations and does not attempt to control for unobserved factors that may influence enrollment and COVID policy (Malkus, 2022).

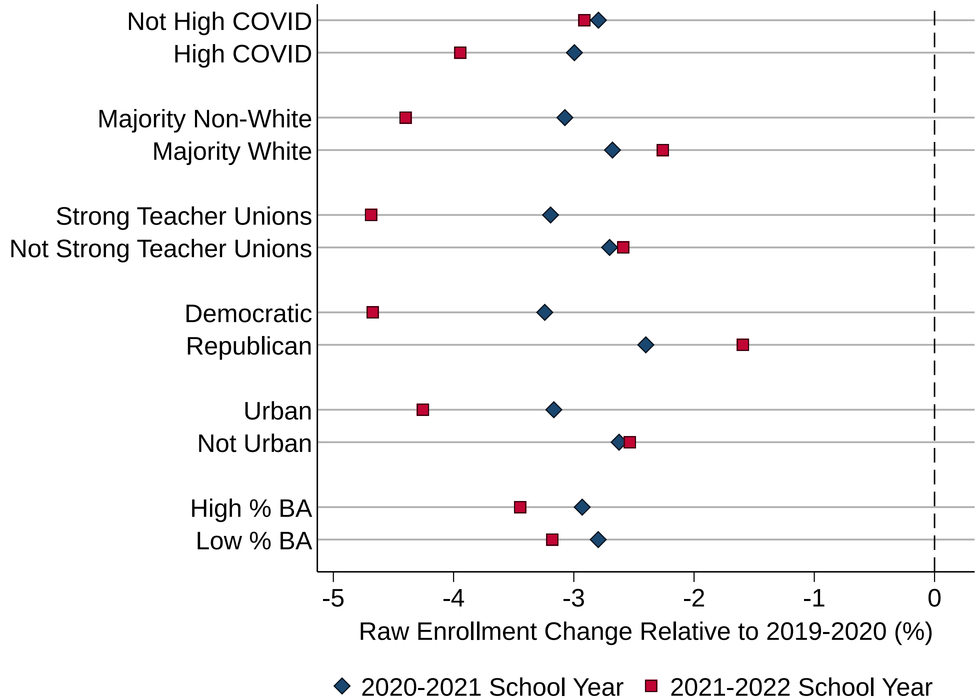
residents of the same cities due to a combination of disproportionate underlying comorbidities, greater employment in occupations with less flexibility to socially distance, and a historically discriminatory U.S. public health system (Hooper et al., 2020; Perry et al., 2021; Zavala et al., 2021). Second, non-White Americans frequently report lower trust in medical and social institutions in general, are less likely to have health insurance and were more wary of in-person learning during the COVID-19 pandemic (Alsan & Wanamaker, 2018; Ariga & Hill, 2022; Kogan, 2021). On the other hand, to the extent that non-White families disproportionately worked in occupations that offered less flexibility to work from home, they may have had less ability to manage virtual instruction, and thus an incentive to prefer in-person schooling.

2 Data and Descriptive Evidence

We combine several public use data sources to construct a sample of districts enrolling more than 90% of all U.S. public school students. We use student enrollment counts from the U.S. Department of Education's Common Core of Data (CCD), restricting our sample to "regular" school districts operating as the region's direct provider of public education. We obtain data on start-of-year learning modes from the COVID-19 School Data Hub (CSDH) and start-of-year mask requirements from the Return to Learn (R2L) tracker (COVID-19 School Data Hub, 2022; Malkus et al., 2023). CSDH defines learning modes as in-person, hybrid, or virtual based on the mode of instruction for the majority of students. In our sample, 27% of districts (enrolling 44% of students) started the 2020-21 year fully virtual while 44% of districts (enrolling 33% of students) started the 2020-21 school year in-person. Virtually every school district was in-person to start the 2021-22 school year; 42% of districts (enrolling 35% of students) started the year without a mask requirement.

We measure pandemic conditions in each school district at the start of the 2020-21 and 2021-22 school years. To measure COVID-19 severity, we use county-level COVID deaths

Figure 1. Distribution of COVID-19 Enrollment Changes by District Characteristics



Note: High COVID is defined as an above-mean county COVID death rate from March-August 2020. Teacher union strength is based on an index from the Fordham Institute (Winkler et al., 2012). Partisanship is based on 2016 presidential election vote shares. Low % BA = districts with less than 25% of adults having a bachelors' degree or more.

per capita from March through August prior to each school year, compiled by The New York Times (The New York Times, 2021). We also include the county's mask-wearing rate (measured in July 2020) and two-dose vaccination rate for individuals 12 and older (measured in July 2021) to capture local COVID precautions. Finally, we utilize a variety of district-level characteristics meant to capture social, economic and political factors that could influence COVID policy and public school enrollment changes (see the Data Appendix). Examples include poverty rates, political partisanship, and racial composition.

2.A Raw Enrollment Changes

Enrollment changes varied dramatically across districts (Figure 1). In 2020-21, enrollments declined more in Democratic and urban places and in places with stronger teacher unions, compared to non-urban areas and places with more Republicans and weaker teacher unions. Moreover, these differences grew *larger* in 2021-22; for example, urban enrollments declined 3.2% in 2020-21 relative to 2019-20 and declined further to 4.3% below pre-COVID levels in 2021-22, while non-urban enrollments declined by 2.6% in 2020-21 but recovered 0.1 percentage points of this decline in 2021-22.

Figure 2 shows how enrollment changes tracked with school learning mode in 2020-21. Focusing on the top set of points that measures raw enrollment changes, we see that virtual, hybrid, and in-person districts lost 3.4%, 3.0%, and 2.0% of their 2019-20 enrollments in the first pandemic school year. That is, as others have noted, districts that only offered virtual instruction saw larger enrollment drops than other districts.

Kindergarten enrollments experienced the largest average declines (10.0%); high school enrollments did not change at all on average. Elementary (grades 1-5) and middle school enrollments declined by 4.2% and 2.2%, respectively. Kindergarten also exhibited the strongest relationship between learning modes and enrollments; enrollments declined 5.7 percentage points more in virtual compared to in-person districts (12.5% vs 6.8%). Elementary and middle school enrollments also declined more in virtual districts, but differences were smaller.

The bottom of Figure 2 looks separately by race. We see that White enrollments declined the most (6.0%), followed by Black (3.7%), Hispanic (3.0%), and Asian enrollments (1.2%). Even more interestingly, we see that White enrollments declined substantially more in districts with virtual instruction compared with hybrid or in-person learning (8.0% vs 4.9%). Black, Hispanic, and Asian enrollments declined slightly more in virtual districts but differences were much smaller.

The raw data in Figure 2 hints at the differential response of age and racial/ethnic groups to school COVID policies. However, school COVID policies were associated with a host of other social, economic and political differences across districts (see Table S1). The most striking differences between in-person, hybrid and virtual districts are demographic and political. The average virtual district was more than twice as large as the average hybrid or in-person district. Virtual districts and those with mask requirements had lower proportions of White students and higher proportions of students eligible for subsidized meals. For example, 38% of students in virtual districts were White compared with 66% in hybrid districts and 55% in in-person districts. Districts offering in-person instruction were more likely to be rural (27%) than those offering hybrid (22%) or virtual (11%) instruction. Finally, virtual districts tended to be more politically liberal; the 2016 Trump vote share in virtual districts was 37% compared with 47% in hybrid and 57% in in-person districts. On the other hand, COVID death rates were similar across districts starting in different learning modes. We observe similar demographic differences between districts that did and did not require masks in fall 2021.

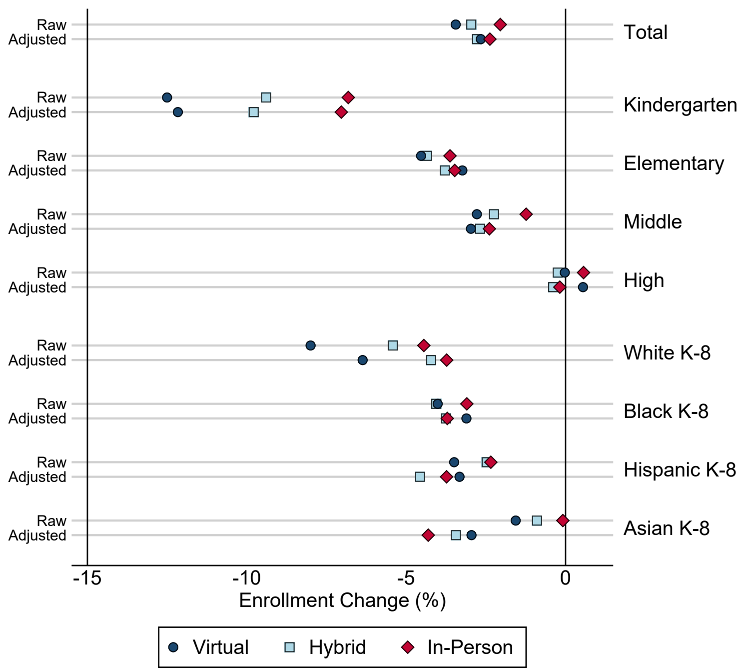
Moreover, state policies also played an important role in determining district policies. For example, Texas and Florida required every district to start in-person in fall 2020 and without masks in fall 2021, while the governors of California and Kentucky required districts to start virtually in fall 2020 in all counties above certain COVID-19 case thresholds (Cowan, 2020; Kobin, 2020; Wamsley, 2020a, 2020b). As exhibited in Figure S1, this geographic variation resulted in many large, urban districts (like Houston and Orlando) starting fall 2020 in-person and small, rural districts (e.g., in California) starting fall 2020 virtually.

3 Overview of Research Design

Our goal is to estimate the causal relationship between school COVID policy and student enrollment, with a particular focus on whether the relationship varied by age and race/ethnicity. The key challenge is that COVID policy was associated with a host of pre-existing and COVID-specific factors (Table S1) that may have influenced enrollment directly. We take several steps to mitigate this concern. We summarize these steps here and provide more details in "Materials and Methods" and in the Methods Appendix.

To begin, we adjust our estimated enrollment declines for pre-COVID enrollment trends,

Figure 2. Change in Enrollment from 2019-20 to 2020-21



Note: "Raw" changes are average enrollment changes from 2019-20 to 2020-21 while "adjusted" changes are relative to pre-existing trends in log enrollments from 2016-2020. Elementary = grades 1-5.

which will be important if districts or specific demographic subgroups were growing at different rates in places that adopted particular COVID policies. Specifically, we estimate the trend in log enrollment for each age and racial group within each district during the five years prior to the COVID-19 pandemic (i.e., from 2015-16 through 2019-20).[2] We then extrapolate from this pre-COVID trend and calculate the deviation from expected log enrollment in the 2020-21 and 2021-22 academic years.[3]

Enrollment had been growing more slowly (and in some cases shrinking) in virtual districts prior to the pandemic. When we account for this, the gap between virtual vs in-person districts in terms of changes in total enrollment disappears (see Figure 2). This adjustment also results in substantively different conclusions about how enrollment changed for different racial/ethnic subgroups. For example, while Black enrollment declines were slightly larger in virtual than in-person districts (left panel), when we account for pre-existing trends we find that Black enrollment declined more for in-person (3.7%) than virtual (3.1%) districts. Looking at deviations from trend more generally, it is clear that White enrollments declined more when instruction was virtual while the reverse was true for non-White enrollments.

For our main analyses, we regress these enrollment deviations on COVID learning policies (learning mode in 2020-21 and mask policy in 2021-22), controlling for local COVID death rates, masking/vaccination rates, and district and area demographic characteristics. In models of overall district enrollment, we also include state fixed effects to account for state-level enrollment changes that could be correlated with learning modes.[4] In models of specific student subgroups (grade level and race/ethnicity), we include district fixed effects, which ensures we are comparing enrollment changes of different groups *within* the same district and allows us to disentangle heterogeneity across student types from heterogeneity across

[2] Enrollment for the 2019-20 school year comes from student counts in October 2019, and thus should not be influenced by COVID.

[3] Because deviations from trend are usually small, less than 10%, we interpret these as percent-deviations.

[4] For example, the rise of remote work enabled some households to make lifestyle-oriented interstate moves from colder, more expensive states to warmer, cheaper states. Because districts in these states also employed different learning modes and mask policies, these changes would bias our coefficients without the inclusion of state fixed effects (Haslag & Weagley, 2022).

district characteristics.[5] Because local characteristics (e.g., COVID death rates and political partisanship) may have affected enrollments of racial/ethnic groups differently, we control for interactions between all covariates and student race/ethnicity. In race/ethnicity models, we also control for race-specific measures of resources and access to non-public schooling options since differences in these characteristics could also lead to different public school disenrollment patterns.

Lastly, we implement an Instrumental Variable (IV) strategy to address any remaining unobserved factors that might bias our estimates. Our approach leverages the variation in state policies requiring certain learning modes or masking rules, in combination with the documented association between certain district characteristics and subsequent policies. The intuition behind our strategy is that districts that were highly likely to impose virtual instruction (e.g., large school systems with active unions or "blue" districts) were less likely to do so if they were located in "red" states, and vice versa. Importantly, our regression models control directly for the district characteristics that predict learning mode as well as local COVID severity and prevention efforts (all interacted with race indicators), which help satisfy the exclusion restriction in these models.

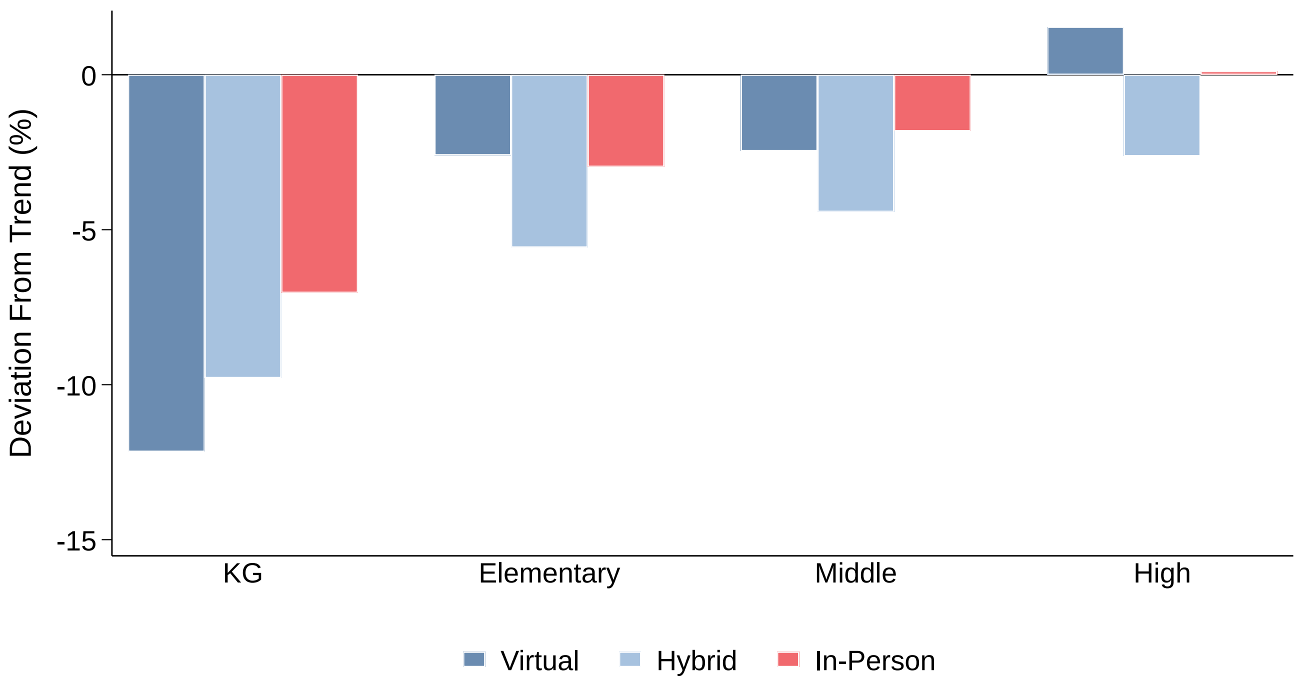
4 Results

4.A Model Estimates of Enrollment Changes in 2020-21

Multivariate regression estimates show that relative to their pre-COVID enrollment trends, districts that started in-person and hybrid experienced smaller enrollment declines in 2020-

[5] The prior research is mixed on whether enrollment declines were larger for White or non-White students, with results sensitive to the the sample and methodology (Chatterji & Li, 2021; Dee et al., 2021; Musaddiq et al., 2022) Moreover, earlier work finds that districts with more Black students may have been less responsive to virtual instruction than districts with fewer Black students (Dee et al., 2021). However, because Black students attend school districts that are different in many ways than those attended by White students, it is challenging to determine if different enrollment patterns are due to differential responses of Black families or to differential responses of all students in districts with a large proportion of Black families.

Figure 3. Predicted 2020-21 Enrollment Changes, by District Policy and Student Age



Note: Elementary = grades 1-5. Bar heights represent the predicted deviation for a district with the national average for all control variables. N = 36,261 for 9,328 districts with at least 10 students in every grade in every year from 2016-2022. See Table S3, column 4 for regression coefficients.

21 compared with districts that started virtually. After controlling for social, political, and economic district characteristics, local COVID severity and prevention measures, and state fixed effects, virtual districts experienced an average enrollment decline of 2.7%, compared with declines of 1.4% and 1.9% for in-person and hybrid districts respectively (Table S2 column 6 contains our preferred specification). The relative differences are quite large, with in-person districts experiencing enrollment declines 48% (0.013 / 0.027) smaller than virtual districts. In comparison to recent US history, these magnitudes are large and meaningful; only twice in the previous 35 years did public school enrollments decline even 1% year-over-year.

Looking separately by age, we see that kindergarten enrollment responded to learning mode much differently than enrollment in other grades. Figure 3 shows the predicted enrollment change in 2020-21 by learning mode and age group based on the model estimates shown in Table S3, column 4. In kindergarten, enrollment declined 43% less in districts with in-person relative to virtual learning (12.2% in virtual compared with in-person declines of 7.0%). In elementary and middle school, the differences in enrollment changes were less consistent and smaller than in kindergarten; high school enrollments changed little. Interestingly, with the exception of kindergarten, our models indicate that enrollment declined the most in districts with hybrid learning mode, suggesting that this "compromise" approach may have been particularly frustrating for families.

As described above, COVID affected racial groups in the U.S. quite differently because of geographic location, occupation, income levels, and institutional trust. Here we examine whether these differences translated into school enrollment. We focus on K-8 enrollment; high school enrollment experienced little change during COVID regardless of learning mode, and there were no notable differences by race.

We find White enrollments responded very differently to school learning mode compared with non-White enrollments. Specifically, White enrollments declined more in districts that adopted virtual instruction; the reverse was true for non-White enrollments. Figure 4 illustrates these differential enrollment responses by plotting the average expected enrollment changes in 2020-21 separately by race and learning mode, based on the model estimates shown in Table S4, column 4.

White enrollment declined 6.4% when districts were virtual. We estimate Black, Hispanic, and Asian enrollment declines were roughly one-half this size in the same districts; these differences were statistically significant at the 1% level for Black students and at the 5% level for Hispanic and Asian students. White enrollment declined significantly less in districts with hybrid (4.2% decline) and in-person (3.7% decline) instruction. Black, Hispanic, and Asian enrollment generally declined *more* when districts adopted in-person instruction. For Black and Hispanic students, in-person enrollments declined the most, followed by hybrid and then virtual enrollments. For Asian students, declines in virtual and hybrid districts were not significantly different, but declines were considerably larger for in-person districts.

These differences are large and highly significant ($p<0.01$; see coefficients on the interaction terms in Table S4). For example, White enrollment declined 2.7 percentage points *less* when the district adopted in-person learning (relative to virtual) while Black enrollment declined 3.1 percentage points *more* under the same scenario. Given average K-8 enrollment declines of roughly 4.1%, differences of these magnitudes reflect relative differences of 66-75%.

Why might non-White families be less likely to enroll in public schools that were operating in-person? One reason might be that these families felt COVID represented a bigger threat to their safety. Age-adjusted death rates from COVID-19 were 65% greater among Black and Hispanic individuals compared to Whites (though Asian and White death rates were similar); moreover, the racial disparity in death rates was largest in the early months of the pandemic, the period relevant to our analysis (Ndugga et al., 2022).

Enrollment responses to local COVID severity provides additional evidence of greater health concerns in non-White communities. Looking within districts and controlling for the differential effects of learning mode as well as other district characteristics, we find that Black, Hispanic and Asian enrollment changes in 2020-21 were more sensitive to local COVID death rates compared with White enrollment. Specifically, a 10% increase in COVID deaths is associated with non-White enrollment declining 0.5-0.7 percentage points *more* than White enrollment. These results are consistent with the story that non-White families were more cautious when faced with the pandemic's health consequences, and for Asian students that this is true even accounting for similar aggregate community risk compared to White students.[6]

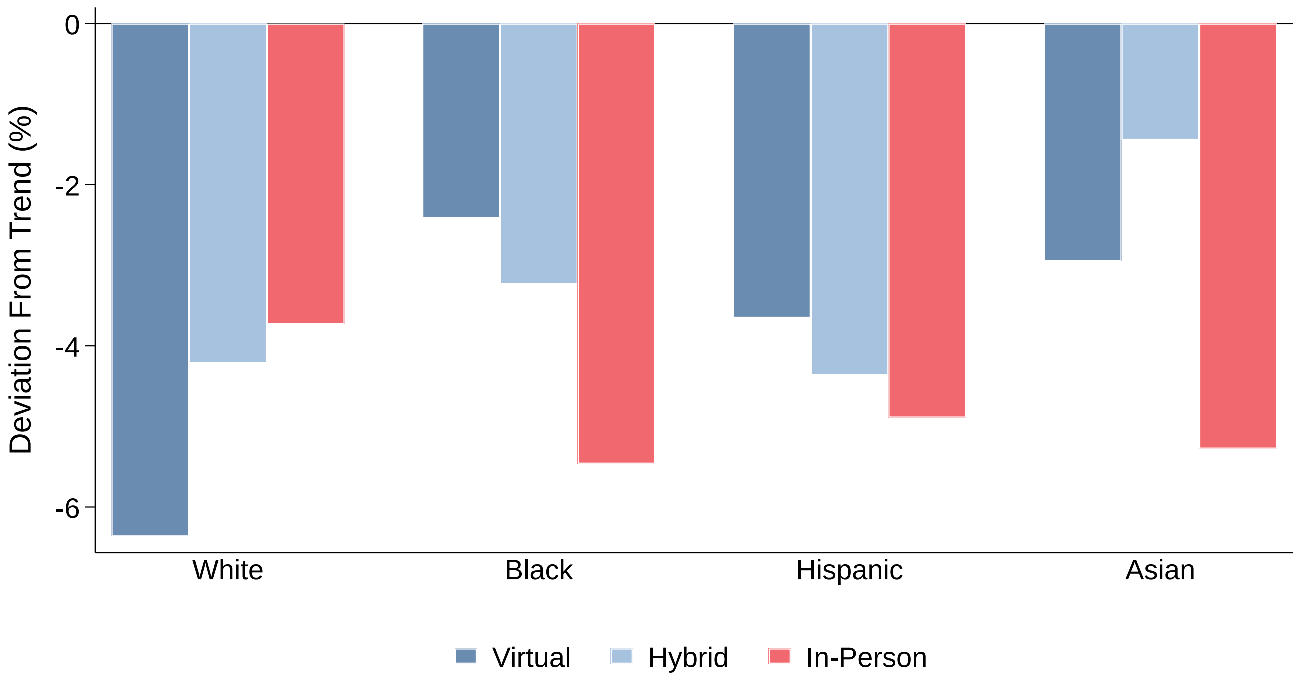
4.B Model Estimates of Enrollment Changes in 2021-22

While nearly all public schools started the 2021-22 school year in-person, roughly one-third required students and staff to wear masks in school. Parents who left their local district in the prior year were faced with the decision to re-enroll their child in 2021-22, or continue with an alternative school arrangement.

We find that the prior year's learning mode as well as the current year's masking policy both influenced district enrollment in 2021-22. Even after controlling for fall 2020 learning mode (and other covariates) districts *without* mask requirements saw 2021-22 enrollment decline 0.8 percentage points (29%) *less* than those with mask requirements. Interestingly, districts that offered in-person and hybrid instruction in 2020-21 experienced larger enrollment rebounds than those districts that offered virtual instruction (Table S5), even when controlling for masking policy and other factors. For example, districts that were in-person in 2020-21 had enrollment declines in 2021-22 that were 0.8 percentage points (29%) less than districts that were virtual in 2020-21; hybrid districts experienced declines 0.7 percentage points (25%) less.

[6] Note that these estimates do not distinguish between enrollment responses to COVID death rates in different learning modes. In exploratory analyses, we found this negative association is present regardless of the district's initial learning mode. While it may seem surprising that families respond to COVID severity in districts with virtual learning, it is important to recognize the uncertainty surrounding school learning mode at this time. Even in districts that started virtually families may have been concerned about returning to in-person learning at some point during the school year. Moreover, our learning mode specific estimates are imprecise, and not always significantly different than zero or significantly different across learning modes.

Figure 4. Predicted 2020-21 Enrollment Changes, by District Policy and Student Race/Ethnicity



Note: Bar heights represent the predicted deviation for a district with the national average for all control variables. Regressions include one observation per district-race-age group (kindergarten, elementary, middle). N = 48,906 observations for 6,876 districts with at least 10 same-age students in two racial/ethnic groups in all years from 2016-2022. See Table S4, column 4 for regression coefficients.

In 2021-22, enrollments remained 2-5 percentage points below trends for K-8 students. We do not identify large age differences in enrollment responses to mask policies in 2021-22 (Table S6). Notably, Kindergarten enrollments did not rebound in 2021-22; if the large 2020-21 declines in K enrollment were due to parents "redshirting" their children for a year, we would expect 2021-22 enrollments to recover considerably. Instead, it appears that a significant number of families permanently moved towards alternative schooling options.

White enrollments remained 5.6% below pre-pandemic trends. Non-White enrollments recovered considerably more than White enrollments in districts with and without mask requirements, though the previous year's learning mode differences persisted (Table S7). Our IV specification indicates Black enrollment declined comparatively more in districts without mask policies; however, this result is not robust to the alternative specifications in columns 1-3.

4.C Sensitivity Analyses

We conduct a variety of sensitivity analyses, all of which support the findings above. First, we confirm that our results are robust to (i) alternative definitions of learning mode; (ii) the sample of districts included in our analysis; and (iii) different ways of calculating pre-pandemic enrollment trends (Tables S8-S10). We also confirm our results are not driven solely by our IV strategy or choice of pre-pandemic control variables. As we show in Tables S2 through S7, the same associations are present in OLS specifications with and without covariates. OLS estimates are smaller in magnitude than the IV estimates, which one would expect if observed learning modes are correlated with unobserved preference for that policy. The OLS estimates suggest that the main difference between White and non-White enrollment changes is how they responded to virtual instruction - namely, White enrollment across all specifications declines substantially more than non-White enrollment in districts with virtual learning.

We found that the enrollment disparities by learning mode we observe in 2020-21 persisted into the following school year. We confirm this result's robustness by 1) running identical 2020-21 specifications with 2021-22 enrollment as the outcome, and 2) omitting summer 2021 COVID death rates from our set of controls in our main 2021-22 specifications (since COVID death rates could themselves be a function of fall 2020 learning mode decisions); see Table S11.

Because Black and Hispanic students disproportionately enroll in charter schools, we examine whether charter enrollment responded differently to COVID policies than public school enrollment. The data on learning modes in charter schools are not as comprehensive as they are for public districts, and we lack data for charter mask policies, but we find that the learning modes adopted by charters usually match those of the nearby district. Due to the small sample sizes and incomplete data, analysis of charter enrollment changes alone are not informative. Instead, we assign all charter schools to their nearest public district and compare whether regional enrollments responded differently than public enrollments alone. Given that we run these models in a sample of only about 800 districts with any nearby charters, magnitudes should be interpreted with caution; however, our results are unchanged and, if anything, point to stronger learning mode differences by race in charters than in public districts (see Table S12).

Finally, non-White Americans are generally more Democratic than the country as a whole. Because partisanship is highly associated with learning mode preferences, these results could theoretically be explained by more Black, Hispanic, and Asian households being Democrats than White households in the same districts. However, our point estimates are similar (albeit with varied statistical precision) when we do not control for district partisanship and when we estimate models in the subset of districts where more than two-thirds of respondents voted for Hillary Clinton in the 2016 election (Table S13). This suggests differential partisanship alone is not enough to explain our findings.

5 Discussion

This paper examines the association between school COVID-19 policies and enrollment changes, with a particular focus on how responses differed across student subgroups. We document several important findings. First, overall enrollment declines were larger in districts imposing more stringent COVID policies such as virtual-only instruction and mask requirements. Second, enrollment responses to COVID policies differed substantially by age. Not only were enrollment declines larger among kindergarten and elementary children, but the enrollment of students in younger grades was much more sensitive to learning mode. Third, enrollment responses to learning mode differed notably by race and ethnicity. While White enrollments declined more in districts that started the 2020-21 school year virtually, Black, Hispanic, and Asian enrollments declined more in districts that started the school year in-person. While there is some evidence that Black enrollment declined more than White enrollment in districts with mask optional policies, we do not see a similar difference for Hispanic or Asian enrollments.

Broadly speaking, different enrollment responses across groups could be due to either differences in preferences for learning mode or differences in financial resources or both.[7] The large differences in how racial/ethnic groups responded to virtual learning we saw in Figure 2 raises the possibility that resources constraints may be important. That is, it could be that all families would prefer to avoid remote learning, but White families have greater resources which allow them to attend private schools, move, or transfer to another public district. However, these differences persist in models that control for group-specific measures of median household income and poverty rates in the district, suggesting that resources may not be as important as one might have imagined.

On the other hand, several pieces of evidence suggest that differences in preferences for learning mode - particularly preferences due to perceived health risks - were an important

[7] In theory, it is also possible that the "cost" of particular COVID policies differs across group within the same district because of, for example, differences in school quality.

determinant of enrollment responses. First, our preferred model estimates suggest that enrollment declines in in-person districts were *larger* for non-White than White families. Second, we find that non-White enrollments were more sensitive to local COVID severity, even after controlling for learning mode and a host of other district factors. However, it is also possible that these differences in preferences are instead due to other factors, such as the partisan lean of White vs non-White households as suggested by Kogan (2021).

Finally, our results are consistent with survey evidence that Black and Hispanic parents consistently reported greater reluctance to send their children back in-person (Camp & Zamarro, 2022; Kogan, 2021).[8] To the extent that schools serving more Black and Hispanic students have fewer resources, on average, than other schools in the same district, this perception could have some justification.[9] Notably, we observe much smaller racial differences in actual enrollment outcomes compared to preferences expressed in the surveys cited above, demonstrating the importance of economic and geographic constraints (such as a lack of nearby alternative schooling options) on enrollment decisions.

These findings have important implications for the academic achievement of individual students and the fiscal solvency of school districts. Recent studies document significant learning loss among students who attended school virtually during the 2020-21 school year; these losses persisted at least through the 2021-22 year (Halloran et al., 2023; Jack et al., 2022). If White students who left virtual districts enrolled in charter or private schools that taught their students in-person, or were engaged in a high-quality homeschooling option, the enrollment patterns we document could exacerbate pre-existing racial achievement gaps in these communities (Reardon & Cimpian, 2008). Given that school funding is determined by student enrollment, districts with higher proportions of non-White students that maintained

[8] Kogan (2021) shows that much of this difference can be explained by racial and ethnic sorting across school districts; that is, non-White parents preferred virtual schooling because non-White families tend to live in places that remained virtual for longer. We show that these racial and ethnic differences in preferences exist even within districts.

[9] This finding is also consistent with a lower perceived benefit of in-person instruction among non-White families. However, there is no evidence from academic research or media reports to suggest that this was the case.

in-person instruction during the pandemic will likely face greater fiscal challenges in coming years than in-person districts with a predominantly White student population.

6 Materials and Methods

6.A Sample Definitions

13,038 regular U.S. public school districts operated during the 2020-21 school year. Because our analytic strategy relies on calculating district-specific enrollment trends, we omitted districts with fewer than 10 students per grade per year to avoid overly large year-to-year fluctuations in enrollments. Therefore our sample for 2020-21 contains 9,328 US school districts. Our sample for 2021-22 contains 7,255 districts with mask policy data. Finally, for our race/ethnicity analyses, we omit districts with fewer than 10 students of multiple races/ethnicities (White, Black, Hispanic, and Asian) in all age groups. Our sample is highly representative of the U.S. public school population, though by construction our sample for race/ethnicity models is more diverse (Table S14).

6.B Regression Models

Our goal is to estimate the causal relationship between COVID school policies and differences in student enrollment by race/ethnicity. We take steps to address concerns that 1) districts and demographic groups were growing at different rates in places that adopted different COVID policies, 2) COVID policies were associated with other local and state characteristics, and 3) racial and ethnic groups sort non-randomly across districts in ways that may be correlated with local COVID conditions and policies.

To begin, we estimate the following OLS regression for each district using data from the five school years preceding the pandemic (2015-16 through 2019-20):

$$\ln\mathrm{E}_{dt} = \alpha_{0d} + \alpha_{1d}t + \varepsilon_{dt} \tag{1}$$

where t is a linear measure of academic year. We then calculate each district's log-deviation from its pre-pandemic enrollment trend:

$$\widehat{\ln\mathrm{E}}_{d,Y} = \hat{\alpha}_{0d} + \hat{\alpha}_{1d} \cdot Y \tag{2}$$

$$\widehat{D}_{d,Y} = \ln\mathrm{E}_{d,Y} - \widehat{\ln\mathrm{E}}_{d,Y} \tag{3}$$

where $Y = \{2020\_21, 2021\_22\}$. We regress $\hat{D}$ for district d in year t on COVID policies and other observable district characteristics:

$$\begin{aligned}\widehat{D}_{d,2020\_21} = \alpha_0 &+ \alpha_1\text{In-Person}_d + \alpha_2\text{Hybrid}_d \\ &+ \alpha_3\sinh^{-1}(\text{Deaths})_{dt} + \alpha_4 X_{dt} + \gamma_s + \varepsilon_{dt}\end{aligned} \tag{4}$$

$$\begin{aligned}\widehat{D}_{d,2021\_22} = \alpha_0 &+ \alpha_1\text{Mask-Optional}_d + +\alpha_2\text{In-Person}_d + \alpha_3\text{Hybrid}_d \\ &+ \alpha_4\sinh^{-1}(\text{Deaths})_{dt} + \alpha_5 X_{dt} + \gamma_s + \varepsilon_{dt}\end{aligned} \tag{5}$$

In 2021-22 models, we also control for *last* year's learning mode, since it is likely correlated with both mask policies and 2021-22 enrollment deviations. We control for the inverse hyperbolic sine of the total county COVID deaths per 1,000 residents from March through August prior to the academic year; this functional form accounts for the variable's right-skewness. X is a vector of other district characteristics potentially associated with both learning modes and enrollment changes (e.g., partisanship, urbanicity, student poverty rate). γ_s is a state fixed effect, which we include to account for state-level enrollment changes that could be correlated with learning modes. We present results in which we weight each observation by the district's average enrollment in the pre-pandemic sample years (denoted by N_d) as well as results that are unweighted (see SI). We report robust standard errors.

6.C Instrumental Variables

We develop an instrumental variables (IV) strategy to address the concern that district policies were correlated with strong (unobserved) preferences among local parents, either regarding the safety of in-person learning or the educational impact of virtual learning (see the Methods Appendix for additional details). If these (unobserved) concerns led district leaders to choose policies that families requested, then our estimates of enrollment responses to learning modes and mask policies would be biased towards zero.

Prior research has shown that districts were less likely to offer in-person instruction if they were larger, had stronger teacher unions, had a higher proportion of non-White students, and voted Democratic in the last presidential election (DeAngelis & Makridis, 2021; Grossmann et al., 2021; Singer, 2022). To capture these factors, we estimate a multinomial logit model predicting whether a district will offer in-person or hybrid instruction in 2020-21 (relative to virtual instruction) as a function of district demographics and political partisanship:

$$\mathbb{1}\{\text{In-Person}_{ds}, \text{Hybrid}_{ds}, \text{Virtual}_{ds}\} = \mathrm{A}X_{ds} + \lambda_s + u_{ds} \tag{6}$$

We use an identical specification to predict whether districts required masks in 2021-22:

$$\mathbb{1}\{\text{Mask-Optional}_{ds}, \text{Mask-Required}_{ds}\} = \mathrm{B}X_{ds} + \lambda_s + u_{ds} \tag{7}$$

Using the estimated coefficients from these models (Table S15), we calculate the predicted probability that district d in state s will start in-person or hybrid in fall 2020, or mask-optional in fall 2021.

At the same time, state-level policies imposed different thresholds on COVID cases to open in-person or, in some cases, required certain learning modes or mask rules for all districts; see Figure S1 for maps showing this state-level variation (Cowan, 2020; Kobin, 2020; Wamsley, 2020a, 2020b). To capture these policies, for each district we calculate the fraction of *other* districts in the state which started the year in-person/hybrid or without a mask requirement. We use these two variables as well as their interactions as instruments for learning modes and mask policies. First-stage regressions show that these instruments are strongly associated with actual policies (Table S16).

6.D Student Subgroups

We then estimate Equations 1 through 3 for individual student subgroups within a district. This generates measures of the deviation from prior trend for subgroup g in district d in year t, $\hat{D}_{dgt}$, and corresponding enrollment weights N_{dg}. An important advantage of this approach is that it allows us to compare enrollment trends across racial groups *within* the same school district. For example, to determine whether students of different races/ethnicities respond differently to learning modes, we estimate the following regression:

$$\begin{aligned}\widehat{D}_{dg,2021\_22} = {} & \alpha_{1dgt}\text{In-Person}_d \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\ & + \alpha_{2dgt}\text{Hybrid}_d \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\ & + \alpha_{3dgt}\sinh^{-1}(\text{Deaths})_{dt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\ & + \alpha_{4dgt}\text{X}_{dt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\ & + \alpha_{5dgt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] + \delta_d + \varepsilon_{dgt} \end{aligned} \tag{8}$$

Here the district fixed effect δ_d absorbs the main coefficients for learning mode, COVID deaths, and other area characteristics. White students serve as the reference category, so the coefficients α_{5dgt} represent the difference in enrollment deviations between students in group g in a virtual district relative to White students in the same district, and coefficients α_{1dgt} and α_{2dgt} represent the difference in enrollment deviations between students in an in-person or hybrid district, respectively, and White students in the same district. The interaction terms allow enrollment responses to learning modes, COVID death rates, and district characteristics to vary by race/ethnicity. In these models, we cluster standard errors by district.

Our district-specific and group-specific trends approach has a number of advantages relative to other panel data methods commonly used in the literature. We do not impose a parallel trends assumption implicit in standard differences-in-differences specifications; because enrollments for different racial/ethnic groups were trending differently prior to the pandemic, this assumption is clearly violated. Unlike the "comparative interrupted time series" model used in other work studying COVID enrollment changes (Dee et al., 2021), our method allows enrollment trends to vary within districts in the same treatment status rather than just between statuses. This permits us to study heterogeneity in learning mode preferences and COVID risk aversion holding unobserved district characteristics constant.

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S1 Data Appendix

S1.A Defining Public School Districts

Enrollment data come from the National Center for Education Statistics' Common Core of Data (CCD). We restrict the sample to "regular" districts not part of a supervisory union. These are traditional school districts parents perceive when making schooling decisions and can be organized at various levels depending on local conditions. For example, the sample contains both Charlotte-Mecklenburg Public Schools (a county district) and Detroit Public Schools (a city district), but not Wayne County Intermediate School District, which is one bureaucratic level above Detroit Public Schools.

Some districts in VT, NH, and CA are known as type-2 districts ("regular school districts that are a component of a supervisory union"). These districts have an unusual regulatory structure where each district elects its board members to serve on a supervisory union that oversees not only their own district but other neighboring districts as well. We exclude these districts. We also exclude districts operated by the Bureau of Indian Education, which have a very different administrative structure and enrollment criteria compared to traditional districts.

New York City Public Schools is included in the CCD enrollment files as a set of sub-districts, each considered part of the NYC supervisory union. Because the city operated as a single decision-maker for the purpose of determining COVID policies, we aggregate enrollment counts from each of these sub-districts to the entire city and kept one observation for NYC public schools. Alsea School District (Oregon) is mis-coded as a charter district from 2017 onwards in the CCD directory. We re-coded it as a regular school district and kept it in the dataset.

In the CCD, we identified 13,038 regular public school districts operating during the 2020-21 school year. We omitted 1,770 districts without learning mode data from CSDH, leaving us with 11,268 districts. For our primary analyses, we further restricted the sample to districts enrolling at least 10 students in every grade served in each school year from 2015-16 through 2021-22. Because our analytic strategy relies on calculating district-specific enrollment trends, we omitted smaller districts to avoid overly large year-to-year fluctuations in enrollments. Therefore our 2020-21 analytic sample contains 9,328 US school districts, each serving at least 10 students per grade in each year from 2015-16 to 2021-22. Our analytic sample for 2021-22 contains 7,255 districts fitting these sample criteria with mask policy data compiled by R2L. Finally, for our race/ethnicity analyses, we restrict the above sample to districts with at least 10 students of multiple races/ethnicities (White, Black, Hispanic, and Asian) in each age group in all sample years. Table S14 compares our analytic sample to the full sample of US public school districts.

S1.B Validating Enrollment Data

Our primary specifications fit a linear trend to district enrollments from 2015-16 to 2019-2020 and then extrapolate from these trends to predict enrollments in 2020-21 and 2021-22 in the absence of the pandemic. We also undertake the same procedure for students of different racial/ethnic groups within districts. Given this, any misreported enrollments in the pre-pandemic period could lead to spurious pre-trends and miscalculations of our key dependent variable, the percent-deviation of a district's enrollment from this pre-existing trend. It is also important to verify whether, when unexpectedly large changes in enrollments occurred, they were concentrated among specific racial/ethnic groups of students.

For every district in our primary analytic sample (9,328 districts with at least 10 students in every grade in every year from 2015-16 to 2021-22) we identified districts with a >10 percent change in enrollment relative to the previous school year (positive or negative) in any year from 2017-2020. This occurred in 6.8% of districts in our sample (N = 632). If we look at even larger enrollment changes (>20%), these occurred for 2.1% of districts in our sample (N = 192).

Seven states (AZ, CA, IN, ME, ND, NJ, NV) had more than 10% of district experience deviations larger than 10% at any point from 2016-2020. We do not consider ND and NV to be states of concern because 1) the proportion of districts with large changes was not huge (11.4% for ND, 13.3% for NV), 2) large changes were not concentrated in any single year, and 3) they have very few total districts in our analytic sample due to the states' populations and lack of learning mode data.

In the remaining states, large changes were concentrated in a single school year, suggesting a change in either data collection of CCD data reporting behavior. In AZ, 43% of large changes occurred in 2018; in CA, 56% occurred in 2019; in IN, 93% occurred in 2018; in ME, 90% occurred in 2019; and in NJ, 68% occurred in 2017. Large changes in these states/school years comprise 31% of all large changes in any state/year.

However, even in these states in the year of concern, a large majority of districts did not experience these large changes to enrollments; in AZ in 2018, 13% of districts experienced a large change. In CA in 2019, 13% did; in IN in 2018, 25%; in ME in 2018, 17%; and in NJ in 2017, 14%.

We studied how often these sharp enrollment changes are due to single-year measurement error versus a sustained change in how that district's enrollments were reported or recorded. Most of the time, enrollments remained close to their new level in subsequent school years. For 70% of districts with an enrollment change of at least +/- 10%, enrollment remained 10% above/below their previous level in the following school year as well. This is especially true in the five state-years flagged as especially unusual; 92% of districts in these state-years who experienced a large change remained +/-10% from their previous enrollment levels after an additional year.

Lastly, our main results consider relative enrollment changes within districts for students of different races/ethnicities. Given this, it is important to know whether changes in reported enrollments in states/years of concern were consistent across White, Black, Hispanic, and Asian students within districts. Of the districts in our race analyses with a large deviation for the entire district, 61% experienced large changes for all four racial/ethnic groups, 28% for three of the four, 10% for two, and 1% for only one group.

S1.C Learning Modes

We use modality data from the COVID-19 School Data Hub (CSDH). CSDH defines learning modes in the following way:

- **In-person:** Fully in-person instruction 5 days a week for all or most students.
- **Hybrid:** A blend or combination of in-person and virtual instruction for all or the majority of students.
- **Virtual:** Fully remote or distance learning for all or the majority of students.

We focus on the district's first learning mode observed in the 2020-21 school year. Starting mode is very highly correlated with total time spent in the learning mode during the academic year. Moreover, because the enrollment data we use is derived from student counts in October, initial learning mode is the most relevant for our analysis.

21 states reported modality data at the district level, with 34 reporting at the school level (9 states report both). Five states reported no modality data: DE, IA, MT, OK, TN. For districts reporting at the school-level, we follow the CSDH method and assign a given mode to each district if the majority of their students (>50 percent) were enrolled in a school providing that learning mode at that reporting period. In the rare district where no learning mode was the majority (either a perfect 50-50 student split, or a 3-way split with none taking the majority), we define these districts as hybrid.

We collect learning mode for elementary, middle, and high school students for the 18 states that report modes separately by age. We have learning mode data at the elementary school level for 2,929 districts, at the middle school level for 4,379 districts, and at the high school level for 3,467 districts. Within districts, learning modes were usually the same across levels. 93% of districts had the same starting mode for all ages. 96% had the same start mode for elementary/middle school, 96% for middle/high school, and 93% for elementary/high school.

Because the start mode categorization is relatively coarse (more than half of students in a learning mode), we studied how frequently districts enrolled a large proportion of students in multiple modes contemporaneously. In the subset of states with school-level learning mode data, almost all districts (91.3 percent) started all schools in the same learning mode. This was especially true for in-person (92.9 percent) and virtual (94.9 percent).

In sensitivity analyses, we supplement CSDH data with learning mode data collected by MCH Strategic Data. MCH surveyed school districts on their learning modes twice during the 2020-21 school year, in the Fall and the Spring. MCH data differ on some dimensions from CSDH; notably, MCH is much more liberal with their definition of hybrid learning. Because CSDH uses learning mode data and definitions derived from state government sources, we primarily use their data but check the robustness of our results to using MCH data in Tables S8 through S10.

S1.D Mask Policies

Mask policy data comes from the Return to Learn Tracker (R2L, Malkus et al. 2023). R2L collected mask policies by scraping weekly data from public school websites beginning in August 2021. They classified districts as "masks required" or "masks optional." For similar reasons to those for learning modes, we use each district's first mask policy observed in Fall 2021. R2L only collected data for districts with at least three schools, which is why our 2021-22 sample is slightly smaller than our 2020-21 sample.

S1.E District Demographic Characteristics

We use demographic data from two sources: the CCD membership file and the Stanford Education Data Archive (SEDA) covariates file. CCD demographics include the percent of students who are female, White, Black, Hispanic, Asian, and other race. SEDA demographics include the district's mean standardized test scores, percent free-reduced lunch, ELL, segregation index, log median household income, percent adults with a bachelor's degree, and poverty rate.[1] The neighborhood demographics come from matching American Community Survey (ACS) data to district shapefiles. SEDA covariates are missing for 493 districts (3.8 percent). For these districts, we impute covariate values with the county-level equivalents.

In our race/ethnicity models, we include controls for the following race-specific variables: log median household income, poverty rate, proportion of adults with at least a college degree, and 2019-20 area enrollment share in charter schools. We calculate charter school enrollment shares by assigning all charter schools inside each district's catchment zone to that district and calculating the race-specific share of all public + charter enrollment in a charter school. The other three variables are missing for approximately 13 percent of district-race group observations; this is because the ACS masks variables for cells with very few respondents for confidentiality reasons. For these observations, we regress the variable of interest on district race/ethnicity, proportion of students who receive free or reduced price lunch or are English language learners, test scores, within-school segregation indices, Trump 2016 vote share, urbanicity, overall household income, overall poverty rate, and the value of the variable for *other* races/ethnicities in the district.[2] We then take the predicted values for each district-race and assign that value as the race-specific measure. Our results are robust to imputing with the district's overall value instead.

SEDA harmonizes standardized test scores for students in grades 3-8 to a single comparable metric. We calculated a single metric for the district's test scores by averaging all grade-subject test scores (English/math), weighting each grade-subject estimate by a measure of its relative precision, the inverse of its standard error. We used the most-recent available test scores; 86% of scores are from 2018, 4% from 2017, 5% from 2014, with a smattering from all earlier years. AK, AZ, MD, and NY districts are missing all test scores from 2018; most AK test scores are imputed from 2015, AZ scores from 2017, MD scores from 2017, and NY scores from 2014. SEDA does not report test scores for all districts; for example, they exclude all test scores from any state-year when state participation in standardized test subject was <95 percent. In our dataset, 89.4% of districts serving students in grades 3-8 have test scores.

[1] SEDA calculates each district's "information theory index" to measure within-district segregation. The index is defined as the average deviation of each student's school racial diversity from the district-wide racial diversity, where 0 indicates no segregation and 1 indicates complete segregation.

[2] For example, if the variable is "White household income" these other-race values would be "Black household income, Hispanic household income, Asian household income. To keep all observations in regressions, we impute the other-race outcomes of interest with district overall values when necessary and impute dependent variables with county-level measures when available (we include indicators denoting these observations in our regressions).

S1.F Union Strength

To measure the strength of teacher unions in each state, we use an index developed by researchers at the Fordham Institute (Winkler et al., 2012). For other uses of this index, see DeAngelis and Makridis (2021) and Brunner et al. (2020). The index averages scores from five areas of teacher union influence:

1. Members and Resources: includes percentage of teachers in a union, total yearly revenue for state NEA/AFT, state's normalized annual K-12 budget

2. Politics: includes relative political contributions to state candidates from unions and percentage of state convention delegates who are teachers

3. Bargaining: legality of collective bargaining (CB), topics covered by CB (index of 21 topics), whether the state is RTW, whether teachers can strike

4. Policies: use of performance pay, employer-employee pension contribution ratio, whether evaluations can be used for dismissal, whether student achievement is a component of evaluations, teacher tenure strength, criteria for layoffs and dismissal, class size restrictions, charter school policy

5. Reputation: aggregated results from surveys of state education insiders on topics including: the relative influence of teachers' unions, union influence on party platforms, union effectiveness at protecting interests, how hard unions fight for desired policies

The original index used data from 2007-11 and some states have experienced changes to teacher union bargaining power since then (for example, Wisconsin passed Act 10 in 2011, which banned collective bargaining for public-sector unions). We re-collected the variables included in the Fordham bargaining sub-score and re-calculate the index values. The index includes whether CB is legal, whether teachers can strike, RTW status (coded as 0 = RTW, 4 = non-RTW), and indicators for 15 areas over which teachers can bargain (0 = cannot bargain, 4 = can bargain). We average these four scores to get the final score, which ranges from 0-4 (mean 2.03, median 1.84, IQR 1.16-2.83). Our version of the Fordham index has a correlation of 0.99 with the older version; the newer bargaining sub-score has a correlation of 0.93 with the older sub-score.

S1.G Partisanship

We calculate district-level Republican vote shares in the 2016 presidential election using district and precinct shapefiles and precinct-level voting results compiled by the Harvard Voting and Election Science Team. Construction happens in two stages, the first in ArcGIS and the second in Stata. In the first stage, we overlay district and precinct shapefiles and identify every precinct-district overlapping geography. In the second stage, we use the area of each precinct-district overlap to calculate district-level Republican vote shares as a weighted average of the Republican votes cast in all precincts overlapping with that district.

The algorithm works as follows. Say there are N districts (indexed by j) with at least some overlap with precinct i. The total area of precinct i in all districts is:

$$\text{area}_i = \sum_{j=1}^{N} \text{area}_{ij}$$

and the area of precinct i in area j is area_{ij}. Then, the fraction of precinct i's area contained in district A is $\frac{\text{area}_{iA}}{\sum_{j=1}^{N} \text{area}_{ij}}$. We assign shares of precinct vote totals to districts in proportion to this fraction:

$$\text{votes}_{iA} = (\text{total votes in precinct } i) \cdot \frac{\text{area}_{iA}}{\sum_{j=1}^{N} \text{area}_{ij}}$$

District A's total votes from all precincts is then:

$$\text{TotalVotes}_A = \sum_{k \in supp(\text{overlap}_{kA})} \left[(\text{total votes in precinct } k) \cdot \frac{\text{area}_{kA}}{\sum_{j=1}^{N} \text{area}_{kj}} \right]$$

Analogously, district A's Republican vote total from all precincts is:

$$\text{RepVotes}_A = \sum_{k \in supp(\text{overlap}_{kA})} \left[(\text{Republican votes in precinct } k) \cdot \frac{\text{area}_{kA}}{\sum_{j=1}^{N} \text{area}_{kj}} \right]$$

The district's Republican vote share is

$$\text{RepubVoteShare} = \frac{\text{RepVotes}_A}{\text{TotalVotes}_A}$$

Some district boundaries are defined such that their catchment zones overlap. This is particularly common in California, Arizona, Illinois, and Montana, where there are sometimes separate "elementary" and "high school" districts that serve the same students. For some precincts in these states, $\sum_{j=1}^{N} \text{area}_{ij}$ is greater than the actual precinct area. This would result in us assigning fewer votes to each district from that precinct than we would otherwise because we would be dividing by too large a denominator. Therefore, for any precincts where the sum of their precinct-overlap areas is greater than the precinct's actual size, we set the denominators to the total area of the precinct, rather than the sum of the overlap areas. The distributions of resulting Republican vote shares in these states for these two methods are remarkably similar.

12,808 districts (98.4 percent) have non-missing partisanship measures. In the average district's geographic catchment zone, 60% of voters supported the Republican in the 2016 election. In the median district, 63% of voters supported the Republican. Since Democratic voters tend to concentrate in cities, it makes sense that the mean/median district vote share is greater than 50 percent. If we weight districts by 2016 student enrollment, then the mean district's Republican vote share was 47% (median: 48 percent). The actual 2016 Republican national vote share was 46.1 percent.

S2 Methods Appendix

S2.A Regression Models

Our broad goal is to characterize enrollment shifts during 2020-21 and 2020-22, with a particular emphasis on estimating the causal effects of district COVID policies such as instructional mode in 2020-21 and masking rules in 2021-22. One key challenge is that pre-pandemic enrollment trends differed across both age groups and districts/states in ways that may be associated with COVID-19 severity and policy response, including decisions regarding in-person schooling and masking. A related challenge is that unobservable factors orthogonal to district characteristics may have simultaneously influenced district policies and enrollment (e.g., parent concerns about health, responsiveness of local school board members, etc.)

To address these concerns, we combine panel data methods with an instrumental variables approach. Following Dee et al. (2021), we focus on the extent to which a district's enrollment following the start of COVID deviated from its prior trend. Unlike these authors, however, we estimate a fully flexible model in which we allow each district to have a unique enrollment level *and* prior trend. We then compare each district's actual enrollment in 2020-21 and 2021-22 with its *predicted* enrollment, which is determined as a function of its own prior enrollment trend.

Specifically, we estimate the following OLS regression for each district using data from the five school years preceding the pandemic (2015-16 through 2019-20):

$$\ln\mathrm{E}_{dt} = \alpha_{0d} + \alpha_{1d} t + \varepsilon_{dt} \tag{S1}$$

where t is a linear measure of academic year. We then calculate each district's log-deviation from its pre-pandemic enrollment trend.

$$\widehat{\ln\mathrm{E}}_{d,Y} = \hat{\alpha}_{0d} + \hat{\alpha}_{1d} \cdot Y \tag{S2}$$

$$\widehat{D}_{d,Y} = \ln\mathrm{E}_{d,Y} - \widehat{\ln\mathrm{E}}_{d,Y} \tag{S3}$$

where $Y = \{2021\_22, 2021\_22\}$. Because these deviations are typically small (less than 10%), we interpret the log differences as a percentage deviation from trend.

Examining the distribution of these deviations across districts and over time allows us to characterize the effect of the COVID-19 pandemic on public school enrollment. To explore the factors associated with enrollment changes, we regress $\hat{D}$ for district d in year t on observable district characteristics, which include not only COVID policies, but also relevant social characteristics of the district. In 2022 models, we also control for *last* year's learning mode, since it is likely correlated with both mask policies and 2022 enrollment deviations.

$$\widehat{D}_{d,2020\_21} = \alpha_0 + \alpha_1 \text{In-Person}_d + \alpha_2 \text{Hybrid}_d + \alpha_3 \sinh^{-1}(\text{Deaths})_{dt} + \alpha_4 X_{dt} + \gamma_s + \varepsilon_{dt} \tag{S4}$$

$$\begin{aligned}\widehat{D}_{d,2021\_22} = \alpha_0 &+ \alpha_1 \text{Mask-Optional}_d + +\alpha_2 \text{In-Person}_d + \alpha_3 \text{Hybrid}_d \\ &+ \alpha_4 \sinh^{-1}(\text{Deaths})_{dt} + \alpha_5 X_{dt} + \gamma_s + \varepsilon_{dt}\end{aligned} \tag{S5}$$

We present results in which we weight each observation by the district's average enrollment in the pre-pandemic sample years (denoted by N_d) as well as results that are unweighted.

We report robust standard errors. In the models above, In-Person and Hybrid are binary indicators for the learning mode in which the district started the year, with virtual instruction serving as the omitted category. Mask-Optional indicates a district without an indoor mask mandate. $\sinh^{-1}$(Deaths) is the inverse hyperbolic sine of the total county COVID deaths per 1,000 residents from March through August prior to the academic year of the outcome. $\mathbf{X}$ is a vector of other district characteristics potentially associated with both learning modes and enrollment changes. We include both district characteristics (student race/ethnicity and poverty/English Language Learner status, test scores, and indices of school segregation) and area characteristics (partisanship, urbanicity, teacher union strength, college education rate, median household income, poverty rate, charter school market penetration). For 2020-21 enrollments, we also include the proportion of county residents who always wear a mask when leaving the house; for 2021-22 enrollments, we instead include the county's vaccination rate.[3] γ_s is a state fixed effect, which we include to account for state-level enrollment changes that could be correlated with learning modes.[4]

We then extend this approach to examine enrollment trends for individual student subgroups within a district. Estimating the models in Equations S1 through S3 separately by subgroup generates measures of the deviation from prior trend for subgroup g in district d in year t, $\hat{D}_{dgt}$, and corresponding enrollment weights N_{dg}. An important advantage of this approach is that it allows us to compare enrollment trends across racial groups *within* the same school district. For example, to determine whether White, Black, Hispanic, and Asian students respond differently to learning mode or mask policy, we estimate the following regression models:

$$\begin{aligned}
\widehat{D}_{dg,2020_21} = {} & \alpha_{1dgt}\text{In-Person}_d \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{2dgt}\text{Hybrid}_d \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{3dgt}\sinh^{-1}(\text{Deaths})_{dt}\big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{4dgt}\text{X}_{dt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{5dgt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] + \delta_d + \varepsilon_{dgt} \qquad \text{(S6)} \\
\widehat{D}_{dg,2021_22} = {} & \alpha_{1dgt}\text{Mask-Optional}_d \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{2dgt}\sinh^{-1}(\text{Deaths})_{dt}\big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{3dgt}\text{X}_{dt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] \\
& + \alpha_{4dgt} \cdot \big[\mathbb{1}\{\text{Black}\}, \mathbb{1}\{\text{Hispanic}\}, \mathbb{1}\{\text{Asian}\}\big] + \delta_d + \varepsilon_{dgt} \qquad \text{(S7)}
\end{aligned}$$

The interaction terms allow student responses to learning modes, COVID death rates,

[3] Data on county mask-wearing comes from a cross-sectional New York Times survey conducted in July 2020; we do not have comparable data during summer 2021. The CDC first authorized a vaccine for COVID-19 in December 2020, after 2020-21 enrollments were measured; therefore, we only include vaccinations in the 2021-22 enrollment models

[4] For example, the rise of remote work enabled some households to make lifestyle-oriented interstate moves to warmer states with cheaper housing. Haslag and Weagley (2022), using data from two of the largest US moving companies, found that states including Maine, Florida, and Utah experienced the largest pandemic inflows and states including California, Massachusetts, and Washington experienced the largest outflows. Because districts in these states also employed different learning modes and mask policies, these changes would bias our coefficients without the inclusion of state fixed effects.

and district characteristics to vary by student race/ethnicity. The inclusion of a district fixed effect (δ_d) ensures that we are comparing the enrollment changes of different racial groups within the same district[5]. In our preferred specifications, we weight by the number of students in each student subgroup x district (N_{dg}) and present standard errors that are clustered by district. We use the same approach to examine how the enrollment responses differ by student grade level, comparing Kindergarten students to elementary (grades 1-5), middle school, and high school students.

Here the district fixed effect δ_d absorbs the main coefficients for learning mode, COVID deaths, and other area characteristics. We allow responses to both learning modes and COVID case/death rates to vary by student group. Moreover, we allow White students to serve as the reference category, so the coefficients α_{5dgt} in Equation S6 represent the difference in enrollment deviations between students in group g in a virtual district relative to White students in the same district, and coefficients α_{1dgt} and α_{2dgt} represent the difference in enrollment deviations between students in an in-person or hybrid district, respectively, and White students in the same district. In our race/ethnicity models, the vector of characteristics $\mathbf{X}$ also includes the race-specific measures of resources and charter school access discussed in section S1.E.

Our district-specific and group-specific trends approach has a number of advantages relative to other panel data methods commonly used in the literature. We do not impose a parallel trends assumption implicit in standard differences-in-differences specifications; because enrollments for different racial/ethnic groups were trending differently prior to the pandemic, this assumption is clearly violated. Previous work by Dee et al. (2021) studying enrollment changes in response to district learning modes used what is sometimes referred to as a "comparative interrupted time series" model, in which the average deviation from prior trend in all treatment units is compared with the analogous deviation in control units. Our method allows enrollment trends to vary within districts in the same treatment status rather than just between statuses. This permits us to study heterogeneity in learning mode preferences and COVID risk aversion holding unobserved district characteristics constant.

S2.B Instrumental Variables Approach

By permitting each district and district sub-group to have its own pre-pandemic enrollment trend, we account for one important source of heterogeneity that might be associated with district COVID responses. However, one still might be concerned about unobserved heterogeneity associated with the learning mode decisions made by districts in summer 2020 and/or the masking decisions made by districts in summer 2021. For example, district leaders who were aware of strong (unobserved) health concerns among local parents may decided to start the year with virtual instruction. If these (unobserved) concerns led parents to homeschool their children or send them to a different district, our estimate of the relationship between virtual instruction and enrollment would be negatively biased. To address this remaining source of potential bias, we use an instrumental variables approach that leverages district pre-pandemic demographics and state-level pandemic policies.

Prior research has shown that factors such as size, racial composition, union strength and

[5] We omit state fixed effects from these models since they are absorbed by δ_d.

political partisanship are highly predictive of fall 2020 learning model. Specifically, districts were less likely to offer in-person instruction if they were larger, had stronger teacher unions, had a higher proportion of non-White students, and voted Democratic in the last presidential election (DeAngelis & Makridis, 2021; Grossmann et al., 2021; Singer, 2022). At the same time, we know that state-level factors including partisanship and geographic location also predicted learning mode choices (Cowan, 2020; Kobin, 2020; Wamsley, 2020a, 2020b). To capture these factors, we estimate a multinomial logit model predicting whether a district will offer in-person or hybrid instruction in fall 2020 (relative to virtual instruction) as a function of district demographics and political partisanship.

$$\mathbb{1}\{\text{In-Person}_{ds}, \text{Hybrid}_{ds}, \text{Virtual}_{ds}\} = \mathrm{A}X_{ds} + \lambda_s + u_{ds} \tag{S8}$$

We use an identical specification to predict whether districts required masks in fall 2021:

$$\mathbb{1}\{\text{Mask-Optional}_{ds}, \text{Mask-Required}_{ds}\} = \mathrm{B}X_{ds} + \lambda_s + u_{ds} \tag{S9}$$

These models are not weighted by district enrollment because the district acts as the decision-maker regarding learning modes and mask policies, rather than the household. In order to provide the most comprehensive set of predictions, we estimated the model using all districts with non-imputed learning modes and non-missing mask data, including districts that did not satisfy our minimum enrollment threshold to enter our analytic sample. Appendix Table S15 shows estimated marginal effects evaluated at sample means. Holding other characteristics constant, smaller, more Republican districts with higher standardized test scores and weaker teacher unions were more likely to start in-person than virtual, while larger, less Republican districts were more likely to start hybrid than virtual. Districts without mask requirements were more Republican, had higher standardized test scores, and were located in areas with fewer adults with college degrees and greater charter school penetration.

Using the estimated coefficients on the district characteristics from the models above, we calculate the predicted probability that district d in state s will start in-person (i) as $z_{ds}^{1,i} \equiv \widehat{\text{In-Person}}_{ds} = \widehat{\mathrm{A}^i}X_{ds}$. In the same manner, we calculate the predicted probability that each district will start hybrid (h): $z_{ds}^{1,h} \equiv \widehat{\text{Hybrid}}_{ds} = \widehat{\mathrm{A}^h}X_{ds}$. Finally, we calculate the predicted probability that district was mask-optional (m): $z_{ds}^{1,m} \equiv \widehat{\text{Mask-Optional}}_{ds} = \widehat{\mathrm{B}}X_{ds}$. The two learning mode predicted probabilities are moderately negatively correlated with each other (Figure S2). Predicted probabilities of an in-person start are highly correlated with predicted probabilities of no mask requirement in 2021-22 (Figure S3).

To capture the various state-level factors influencing a district's initial learning mode decision, for each district we calculate the fraction of *other* districts in the state which started the year in-person/hybrid or without a mask requirement. These instruments are calculated as: $z_{ds}^{2,i} = \frac{\sum_{j\neq d}(\text{In-Person}_{js})}{N_s-1}$, $z_{ds}^{2,h} = \frac{\sum_{j\neq d}(\text{Hybrid}_{js})}{N_s-1}$, $z_{ds}^{2,m} = \frac{\sum_{j\neq d}(\text{Mask-Optional}_{js})}{N_s-1}$ where N_s denotes the number of districts d in state s. This leave-one-out estimator is a parsimonious alternative to modeling the multiple factors (some of which may not be easily observable) driving learning mode and mask decisions statewide. Figures S4 and S5 show that the predicted learning mode and leave-one-out instruments are moderately positively correlated. Districts in states where fewer *other* districts started in-person had lower predicted probabilities of starting in-person, based on their pre-pandemic observable characteristics. The same relationship holds for our hybrid instruments.

We use these two variables as well as their interactions as instruments for in-person and hybrid learning in Equations S4 and S6, and for mask-optional policies in Equations S5 and S7. In learning mode models, this gives us six excluded instruments ($z_{ds}^{1,i}, z_{ds}^{2,i}, z_{ds}^{1,i} \times z_{ds}^{2,i}, z_{ds}^{1,h}, z_{ds}^{2,h}, z_{ds}^{1,h} \times z_{ds}^{2,h}$) for our two endogenous regressors ($\text{In-Person}_d, \text{Hybrid}_d$). In mask policy models, this gives us three excluded instruments ($z_{ds}^{1,m}, z_{ds}^{2,m}, z_{ds}^{1,m} \times z_{ds}^{2,m}$) for one endogenous regressor (Mask-Optional_d). First-stage regressions show that these instruments are strongly associated with learning modes and mask policies (Table S16). Our second-stage F-statistics are well above traditional thresholds for relevance used in the literature.

To satisfy the exclusion restriction, our instruments must only affect enrollment changes (relative to prior trend) via the district's learning mode or mask policy. Our first instrument is a summary of a district's observable social, economic and political characteristics. While it is likely that many of these factors are associated with the long-term enrollment trends in a district, it is harder to think why they should be associated with the *deviation* from this trend in fall 2020. One obvious reason would be that COVID-19 disproportionately impacted districts with certain characteristics, and the severity of the pandemic itself (independent of school learning mode) may well have influenced student enrollment in the public schools. For this reason, we control for COVID severity using death rates in the period of time leading up to the new school year. For similar reasons, we include survey data on the proportion of county residents who wore a mask every time they left the house in July of 2020, and the proportion of county residents age 12+ who were vaccinated in August of 2021, as measures of local risk tolerance and health conscientiousness. Public school enrollment has been trending differently across states, including in some ways that might be correlated with school learning mode (for example, southern and southwestern states experienced faster population growth in the 2010s). However, we include state fixed effects, absorbing state-level trends and deviations from trend. Lastly, we control for a range of local characteristics potentially correlated with both our instrument and district enrollment changes. These include the variables from our multinomial logit models and race-specific measures of resources (household income, poverty rate, proportion of adults with a college degree) and charter school access (proportion of 2019-20 area enrollment in a charter school).

S3 Tables and Figures

Table S1. Descriptive Statistics by Learning Mode, Public School Districts in Analytic Sample

Mean (sd)	2020-21 Learning Mode In-Person	Hybrid	Virtual	2021-22 Mask Policy Optional	Required
COVID-19 Environment					
Deaths/1,000 (monthly)	0.072	0.086	0.088	0.067	0.060
	(0.059)	(0.092)	(0.075)	(0.036)	(0.035)
County Mask-Wearing Rate 2020	0.604	0.640	0.707		
	(0.144)	(0.141)	(0.096)		
County Vaccination Rate 2021				0.360	0.560
				(0.256)	(0.182)
District Characteristics					
Prop. White	0.549	0.657	0.379	0.560	0.464
	(0.292)	(0.266)	(0.263)	(0.281)	(0.293)
Prop. Black	0.144	0.123	0.180	0.136	0.167
	(0.150)	(0.147)	(0.212)	(0.153)	(0.197)
Prop. Hispanic	0.268	0.160	0.356	0.264	0.295
	(0.240)	(0.157)	(0.270)	(0.240)	(0.258)
Prop. Asian	0.032	0.054	0.075	0.033	0.066
	(0.050)	(0.073)	(0.102)	(0.051)	(0.095)
Prop. Free Reduced Lunch	0.526	0.451	0.587	0.516	0.542
	(0.199)	(0.237)	(0.237)	(0.206)	(0.244)
Prop. ELL	0.086	0.058	0.128	0.082	0.109
	(0.089)	(0.064)	(0.100)	(0.085)	(0.098)
Mean Test Score	0.024	0.138	-0.080	0.052	-0.024
	(0.305)	(0.337)	(0.381)	(0.289)	(0.393)
White-Black Segregation Index (0-1)	0.132	0.122	0.175	0.120	0.153
	(0.145)	(0.182)	(0.166)	(0.131)	(0.160)
White-Hispanic Segregation Index (0-1)	0.086	0.091	0.144	0.083	0.123
	(0.098)	(0.128)	(0.130)	(0.086)	(0.127)
Area Characteristics					
2016 Trump Vote Share	0.571	0.474	0.367	0.565	0.410
	(0.160)	(0.207)	(0.162)	(0.154)	(0.175)
Teacher Union Strength Score (0-4)	1.585	2.205	2.185	1.543	2.197
	(0.546)	(0.544)	(0.651)	(0.543)	(0.599)
Prop. District Suburban	0.356	0.447	0.437	0.403	0.443
	(0.375)	(0.434)	(0.414)	(0.382)	(0.419)
Prop. District Town	0.144	0.124	0.071	0.152	0.085
	(0.302)	(0.284)	(0.218)	(0.306)	(0.238)
Prop. District Rural	0.270	0.215	0.111	0.249	0.139
	(0.335)	(0.313)	(0.213)	(0.310)	(0.245)
Prop. Adults College Degree	0.275	0.342	0.324	0.282	0.330
	(0.121)	(0.151)	(0.149)	(0.123)	(0.152)
Poverty Rate	0.136	0.116	0.147	0.130	0.139
	(0.058)	(0.063)	(0.073)	(0.060)	(0.072)
Median Household Income	54,947	64,373	60,578	56,415	61,639
	(17,098)	(23,782)	(21,977)	(17,096)	(23,323)
Prop. Area Enrollment in Charters	0.027	0.026	0.052	0.031	0.044
	(0.059)	(0.057)	(0.091)	(0.062)	(0.084)
N Districts	4,152	2,677	2,499	3,078	4,177
N Students	13,757,640	9,582,573	18,516,870	13,940,740	25,843,660

Note: Statistics are weighted by districts' pre-pandemic total enrollment. District and area characteristics are measured prior to the pandemic. COVID deaths are at the county level and are from March-August 2020 for learning mode columns and March-August 2021 for mask policy columns. Sample includes regular public districts with learning mode data available in the COVID-19 School Data Hub that enrolled at least 10 students in every grade in every year from 2016-2022. Nearby charter/private schools are schools within 10 miles of the district. Prop. = proportion, ELL = English Language Learner. District test scores are scaled to a standard normal distribution.

Table S2. 2020-21 Deviations from Pre-Pandemic Enrollment Trend by Learning Mode

	Unweighted			Enrollment-Weighted		
	OLS	OLS	IV	OLS	OLS	IV
Outcome: %-Deviation from Enrollment Trend	No Controls	Controls + FE	Controls + FE	No Controls	Controls + FE	Controls + FE
Start Virtual Mean	**-0.029**	**-0.029**	**-0.029**	**-0.027**	**-0.027**	**-0.027**
Start In-Person	0.009***	0.010***	0.013**	0.003	0.007***	0.013***
	(0.002)	(0.003)	(0.006)	(0.002)	(0.002)	(0.004)
Start Hybrid	0.003**	0.005**	0.008**	-0.001	0.005***	0.008***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Inv. Hyperb. Sine COVID Deaths	0.046***	0.038***	0.039***	0.030***	0.053***	0.056***
	(0.007)	(0.009)	(0.009)	(0.008)	(0.013)	(0.014)
Prop. Always Wear Mask, Jul 2020	-0.016***	-0.001	0.001	-0.004	-0.003	0.002
	(0.004)	(0.008)	(0.008)	(0.006)	(0.009)	(0.009)
Pre-Pandemic Covariates		X	X		X	X
State FE		X	X		X	X
F-Statistic			35.9			39.5
N	9,328	9,328	9,328	9,328	9,328	9,328

Note: * p<0.1, ** p<0.05, *** p<0.01. Dependent variable is the percent-deviation from districts' pre-pandemic enrollment trend, calculated using 2016-2020 log-enrollments. Enrollment weights are the district's total enrollment in 2016-2020. Sample excludes districts with fewer than 10 students in any grade in any year from 2016-2022. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. Inv. Hyper. Sine = Inverse Hyperbolic Sine, Prop. = Proportion, FE = fixed effects. Standard errors are robust.

Table S3. 2020-21 Deviations From Pre-Pandemic Enrollment Trend by Learning Mode and Student Age

Outcome: %-Deviation from Enrollment Trend	OLS	OLS	OLS	IV
KG Virtual Mean	**-0.122**	**-0.122**	**-0.122**	**-0.122**
In-Person (vs Virtual)	0.046***			
	(0.005)			
Hybrid (vs Virtual)	0.020***			
	(0.006)			
Elementary (vs KG)	0.041***	0.041***	0.055***	0.076***
	(0.010)	(0.011)	(0.017)	(0.016)
Elementary * In-Person	-0.046***	-0.047***	-0.035***	-0.055***
	(0.004)	(0.004)	(0.004)	(0.007)
Elementary * Hybrid	-0.025***	-0.026***	-0.024***	-0.054***
	(0.006)	(0.006)	(0.006)	(0.008)
Middle School (vs KG)	0.060***	0.060***	0.065***	0.078***
	(0.010)	(0.010)	(0.016)	(0.016)
Middle School * In-Person	-0.040***	-0.042***	-0.033***	-0.045***
	(0.004)	(0.004)	(0.004)	(0.007)
Middle School * Hybrid	-0.018***	-0.019***	-0.023***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.010)
High School (vs KG)	0.098***	0.096***	0.096***	0.119***
	(0.011)	(0.011)	(0.018)	(0.017)
High School * In-Person	-0.054***	-0.055***	-0.044***	-0.066***
	(0.005)	(0.005)	(0.005)	(0.008)
High School * Hybrid	-0.030***	-0.031***	-0.031***	-0.066***
	(0.006)	(0.007)	(0.006)	(0.011)
Inv. Hyperb. Sine COVID Deaths	0.033			
	(0.031)			
Elementary * IHS COVID Deaths (vs KG)	0.010	0.007	-0.011	-0.004
	(0.030)	(0.031)	(0.026)	(0.026)
Middle School * IHS COVID Deaths (vs KG)	0.034	0.029	0.001	0.006
	(0.030)	(0.030)	(0.026)	(0.026)
High School * IHS COVID Deaths (vs KG)	-0.061**	-0.061*	-0.079***	-0.070**
	(0.031)	(0.031)	(0.030)	(0.029)
District FE		X	X	X
Pre-Pandemic Covariates x Age Group			X	X
F-Statistic				97.2
N District × Age	36,261	36,261	36,261	36,261
N Districts	9,328	9,328	9,328	9,328

Note: * p<0.1, ** p<0.05, *** p<0.01. Pre-pandemic trends are specific to each district-age group. KG = kindergarten, Elementary = grades 1-5. Sample includes districts with at least 10 students in every grade in every year from 2016-2022. Observations are weighted by the district's total enrollment in that age group in 2016-2020. All models control for the proportion of county residents who always wear a mask (July 2020) interacted with age. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S4. 2020-21 Deviations From Pre-Pandemic Enrollment Trend by Learning Mode and Student Race/Ethnicity

Outcome: %-Deviation from Enrollment Trend	OLS	OLS	OLS	IV
White Virtual Mean	**-0.064**	**-0.064**	**-0.064**	**-0.064**
In-Person (vs Virtual)	0.025***			
	(0.002)			
Hybrid (vs Virtual)	0.019***			
	(0.002)			
Black (vs White)	0.032***	0.030***	0.031**	0.051***
	(0.009)	(0.009)	(0.013)	(0.016)
Black * In-Person (vs White)	-0.031***	-0.025***	-0.029***	-0.056***
	(0.004)	(0.003)	(0.004)	(0.007)
Black * Hybrid (vs White)	-0.026***	-0.020***	-0.020***	-0.031***
	(0.004)	(0.004)	(0.004)	(0.006)
Hispanic (vs White)	0.002	0.011	0.020	0.032**
	(0.008)	(0.010)	(0.014)	(0.016)
Hispanic * In-Person (vs White)	-0.027***	-0.019***	-0.024***	-0.040***
	(0.004)	(0.004)	(0.004)	(0.006)
Hispanic * Hybrid (vs White)	-0.030***	-0.022***	-0.017***	-0.026***
	(0.004)	(0.004)	(0.004)	(0.009)
Asian (vs White)	0.010	0.024*	0.024	0.035**
	(0.012)	(0.014)	(0.017)	(0.018)
Asian * In-Person (vs White)	-0.037***	-0.029***	-0.026***	-0.047***
	(0.005)	(0.005)	(0.005)	(0.008)
Asian * Hybrid (vs White)	-0.023***	-0.016***	-0.011**	-0.009
	(0.004)	(0.005)	(0.005)	(0.009)
Inv. Hyperb. Sine COVID Deaths	0.085***			
	(0.012)			
Black * IHS COVID Deaths (vs White)	-0.094***	-0.062***	-0.047**	-0.048**
	(0.023)	(0.021)	(0.020)	(0.021)
Hispanic * IHS COVID Deaths (vs White)	-0.079***	-0.093***	-0.053**	-0.050**
	(0.017)	(0.022)	(0.022)	(0.023)
Asian * IHS COVID Deaths (vs White)	-0.109***	-0.096***	-0.063***	-0.072***
	(0.019)	(0.023)	(0.024)	(0.027)
District FE		X	X	X
Pre-Pandemic Covariates x Race/Ethnicity			X	X
F-Statistic				79.2
N Districts × Race/Ethnicity × Age	48,906	48,906	48,906	48,906
N Districts	6,876	6,876	6,876	6,876

Note: * p<0.1, ** p<0.05, *** p<0.01. Regressions include one observation per district-race-age (kindergarten, elementary, middle). Pre-pandemic trends are specific to each district-race-age group. Sample includes districts with at least 10 same-age students in two racial/ethnic groups in all years from 2016-2022. Observations are weighted by the district's total enrollment in that race-age group in 2016-2020. All models control for the proportion of county residents who always wear a mask (July 2020) interacted with race/ethnicity. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. We also control for race-specific area poverty rate/household income/adults with a college degree, charter school penetration, and indicators for imputed values of these variables. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S5. 2021-22 Deviations from Pre-Pandemic Enrollment Trend by Mask Policy

	Unweighted			Enrollment-Weighted		
	OLS	OLS	IV	OLS	OLS	IV
Outcome: %-Deviation from Enrollment Trend	No Controls	Controls + FE	Controls + FE	No Controls	Controls + FE	Controls + FE
Masks Required Mean	**-0.023**	**-0.023**	**-0.023**	**-0.028**	**-0.028**	**-0.028**
2022 Masks Optional	-0.002	0.003	0.010**	0.001	0.005**	0.008**
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)
2021 In-Person	0.015***	0.012***	0.011***	0.010***	0.009***	0.008***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
2021 Hybrid	0.008***	0.007**	0.006**	0.004	0.007***	0.007***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Inv. Hyperb. Sine COVID Deaths	0.046**	0.042	0.041	0.115***	0.047*	0.046*
	(0.022)	(0.028)	(0.028)	(0.029)	(0.027)	(0.027)
Prop. Vaccinated, Aug 2021	-0.005	0.021	0.022	0.011*	0.022*	0.022*
	(0.005)	(0.016)	(0.016)	(0.006)	(0.013)	(0.013)
Pre-Pandemic Covariates		X	X		X	X
State FE		X	X		X	X
F-Statistic			195.5			40.4
N	7,255	7,255	7,255	7,255	7,255	7,255

Note: * p<0.1, ** p<0.05, *** p<0.01. Dependent variable is the percent-deviation from districts' pre-pandemic enrollment trend, calculated using 2016-2020 log-enrollments. Enrollment weights are the district's total enrollment in 2016-2020. Sample excludes districts with fewer than 10 students in any grade in any year from 2016-2022. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. Inv. Hyper. Sine = Inverse Hyperbolic Sine, Prop. = Proportion, FE = fixed effects. Standard errors are robust.

Table S6. 2021-22 Deviations From Pre-Pandemic Enrollment Trend by Mask Policy and Student Age

Outcome: %-Deviation from Enrollment Trend	OLS	OLS	OLS	IV
KG Masks Required Mean	**-0.049**	**-0.049**	**-0.049**	**-0.049**
2022 Masks Not Required	0.003			
	(0.004)			
2021 In-Person	0.032***			
	(0.005)			
2021 Hybrid	0.027***			
	(0.005)			
Elementary (vs KG)	0.009	0.01	-0.007	-0.008
	(0.008)	(0.008)	(0.019)	(0.019)
Elementary * 2022 No Masks	0.003	0.003	0.008*	0.015*
	(0.004)	(0.004)	(0.004)	(0.008)
Elementary * 2021 In-Person	-0.018***	-0.019***	-0.006	-0.008
	(0.005)	(0.005)	(0.005)	(0.006)
Elementary * 2021 Hybrid	-0.019***	-0.021***	-0.008*	-0.009*
	(0.005)	(0.006)	(0.005)	(0.005)
Middle School (vs KG)	-0.008	-0.007	-0.017	-0.017
	(0.008)	(0.008)	(0.025)	(0.025)
Middle School * 2022 No Masks	-0.006	-0.006	0.001	0.005
	(0.004)	(0.004)	(0.004)	(0.009)
Middle School * 2021 In-Person	-0.015***	-0.017***	-0.004	-0.005
	(0.006)	(0.006)	(0.005)	(0.006)
Middle School * 2021 Hybrid	-0.015**	-0.017**	-0.005	-0.006
	(0.006)	(0.007)	(0.005)	(0.005)
High School (vs KG)	0.064***	0.065***	0.024	0.023
	(0.008)	(0.008)	(0.029)	(0.028)
High School * 2022 No Masks	-0.005	-0.005	0.003	0.012
	(0.005)	(0.005)	(0.004)	(0.010)
High School * 2021 In-Person	-0.042***	-0.043***	-0.023***	-0.026***
	(0.006)	(0.007)	(0.005)	(0.006)
High School * 2021 Hybrid	-0.041***	-0.042***	-0.020***	-0.021***
	(0.008)	(0.008)	(0.005)	(0.006)
Inv. Hyperb. Sine COVID Deaths	0.158***			
	(0.049)			
Elementary * IHS COVID Deaths (vs KG)	-0.052	-0.052	0.119**	0.124**
	(0.049)	(0.050)	(0.051)	(0.052)
Middle School * IHS COVID Deaths (vs KG)	-0.098*	-0.096*	0.108*	0.111*
	(0.053)	(0.055)	(0.057)	(0.057)
High School * IHS COVID Deaths (vs KG)	0.005	-0.001	0.066	0.072
	(0.060)	(0.060)	(0.061)	(0.061)
District FE		X	X	X
Pre-Pandemic Covariates x Age			X	X
F-Statistic				52.3
N District × Age	28,597	28,597	28,597	28,597
N Districts	7,255	7,255	7,255	7,255

Note: * p<0.1, ** p<0.05, *** p<0.01. Pre-pandemic trends are specific to each district-age group. KG = kindergarten, Elementary = grades 1-5. Sample includes districts with at least 10 students in every grade in every year from 2016-2022. Observations are weighted by the district's total enrollment in that age group in 2016-2020. All models control for the proportion of county residents who were vaccinated against

COVID-19 in August 2021 interacted with age. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S7. 2021-22 Deviations From Pre-Pandemic Enrollment Trend by Mask Policy and Student Race/Ethnicity

Outcome: %-Deviation from Enrollment Trend	OLS	OLS	OLS	IV
White Masks Required Mean	**-0.056**	**-0.056**	**-0.056**	**-0.056**
2022 Masks Optional	0.003			
	(0.003)			
2021 In-Person (vs Virtual)	0.041***			
	(0.003)			
2021 Hybrid (vs Virtual)	0.031***			
	(0.003)			
Black (vs White)	0.039***	0.059***	0.031	0.028
	(0.011)	(0.011)	(0.019)	(0.019)
Black * 2022 Masks Optional	-0.004	-0.006	-0.006	-0.037***
	(0.005)	(0.005)	(0.005)	(0.013)
Black * 2021 In-Person (vs White)	-0.038***	-0.043***	-0.030***	-0.021**
	(0.007)	(0.006)	(0.006)	(0.008)
Black * 2021 Hybrid (vs White)	-0.031***	-0.034***	-0.021***	-0.015**
	(0.006)	(0.006)	(0.006)	(0.007)
Hispanic (vs White)	0.042***	0.054***	0.046**	0.047**
	(0.009)	(0.010)	(0.021)	(0.021)
Hispanic * 2022 Masks Optional	0.007	0.009	0.015*	0.008
	(0.008)	(0.009)	(0.007)	(0.012)
Hispanic * 2021 In-Person (vs White)	-0.051***	-0.052***	-0.037***	-0.035***
	(0.010)	(0.011)	(0.008)	(0.009)
Hispanic * 2021 Hybrid (vs White)	-0.044***	-0.038***	-0.024***	-0.022***
	(0.007)	(0.008)	(0.006)	(0.006)
Asian (vs White)	0.004	0.008	0.061**	0.062**
	(0.015)	(0.014)	(0.025)	(0.025)
Asian * 2022 Masks Optional	-0.001	0.003	-0.002	-0.011
	(0.008)	(0.008)	(0.008)	(0.019)
Asian * 2021 In-Person (vs White)	-0.046***	-0.042***	-0.024***	-0.021*
	(0.008)	(0.008)	(0.009)	(0.011)
Asian * 2021 Hybrid (vs White)	-0.039***	-0.038***	-0.029***	-0.028***
	(0.007)	(0.007)	(0.007)	(0.007)
Inv. Hyperb. Sine COVID Deaths	0.074**			
	(0.033)			
Black * IHS COVID Deaths (vs White)	-0.084	-0.097	0.015	-0.016
	(0.077)	(0.067)	(0.071)	(0.074)
Hispanic * IHS COVID Deaths (vs White)	-0.025	0.004	0.096	0.088
	(0.059)	(0.073)	(0.067)	(0.065)
Asian * IHS COVID Deaths (vs White)	0.149	0.161*	0.08	0.069
	(0.102)	(0.094)	(0.093)	(0.095)
District FE		X	X	X
Pre-Pandemic Covariates x Race/Ethnicity			X	X
F-Statistic				13.2
N Districts × Race/Ethnicity × Age	45,182	45,182	45,182	45,182

N Districts	5,999	5,999	5,999	5,999

Note: * p<0.1, ** p<0.05, *** p<0.01. Regressions include one observation per district-race-age (kindergarten, elementary, middle). Pre-pandemic trends are specific to each district-race-age group. Sample includes districts with at least 10 same-age students in two racial/ethnic groups in all years from 2016-2022. Observations are weighted by the district's total enrollment in that race-age group in 2016-2020. All models control for the proportion of county residents who were vaccinated against COVID-19 in August 2021 interacted with race/ethnicity. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. We also control for race-specific area poverty rate/household income/adults with a college degree, charter school penetration, and indicators for imputed values of these variables. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S8. Sensitivity of Results for 2020-21 Total Enrollment Deviations

Outcome: %-Deviation from Enrollment Trend	Main Results	Impute Learning Modes	No Minimum Grade Size	2012-2020 Linear Enrollment Trends	2012-2020 Quadratic Enrollment Trends
Start Virtual Mean	**-0.027**	**-0.027**	**-0.025**	**-0.044**	**-0.020**
Start In-Person	0.013***	0.013***	0.012***	0.017***	0.009**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Start Hybrid	0.008***	0.007***	0.008***	0.008**	0.007**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Inv. Hyperb. Sine COVID Deaths	0.056***	0.058***	0.054***	0.049***	0.046**
	(0.014)	(0.013)	(0.013)	(0.015)	(0.019)
Prop. Always Wear Mask, Jul 2020	0.002	-0.002	0.007	0.003	0.000
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Pre-Pandemic Covariates	X	X	X	X	X
State FE	X	X	X	X	X
F-Statistic	39.5	39.2	40.2	39.1	39.1
N	9,328	10,315	10,983	9,121	9,121

Note: * p<0.1, ** p<0.05, *** p<0.01. First column shows the main paper results (from Table S2, column 6). Second column includes additional districts with learning modes from a different source, MCH Strategic Data. Third column removes the restriction that districts have at least 10 students per grade in all years from 2016-2022. Fourth and fifth columns calculate pre-COVID enrollment trends using data from 2012-2020 (rather than 2016-2020). In all models, enrollment weights are the district's total enrollment in the relevant pre-COVID period. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. Inv. Hyper. Sine = Inverse Hyperbolic Sine, Prop. = Proportion, FE = fixed effects. Standard errors are robust.

Table S9. Sensitivity of Results for 2020-21 Enrollment Deviations by Age

Outcome: %-Deviation from Enrollment Trend	Main Results	Impute Learning Modes	No Minimum Grade Size	2012-2020 Linear Enrollment Trends	2012-2020 Quadratic Enrollment Trends
KG Virtual Mean	**-0.122**	**-0.121**	**-0.119**	**-0.135**	**-0.109**
Elementary (vs KG)	0.076***	0.078***	0.074***	0.051***	0.076***
	(0.016)	(0.015)	(0.016)	(0.017)	(0.016)
Elementary * In-Person	-0.055***	-0.056***	-0.055***	-0.069***	-0.056***
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)
Elementary * Hybrid	-0.054***	-0.052***	-0.055***	-0.069***	-0.057***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)
Middle School (vs KG)	0.078***	0.075***	0.074***	0.062***	0.069***
	(0.016)	(0.015)	(0.017)	(0.017)	(0.016)
Middle School * In-Person	-0.045***	-0.044***	-0.045***	-0.061***	-0.044***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Middle School * Hybrid	-0.043***	-0.044***	-0.044***	-0.045***	-0.047***
	(0.010)	(0.010)	(0.010)	(0.008)	(0.012)
High School (vs KG)	0.119***	0.120***	0.114***	0.111***	0.112***
	(0.017)	(0.016)	(0.018)	(0.019)	(0.018)
High School * In-Person	-0.066***	-0.067***	-0.067***	-0.082***	-0.066***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
High School * Hybrid	-0.066***	-0.063***	-0.067***	-0.077***	-0.070***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.013)
Elementary * IHS COVID Deaths (vs KG)	-0.004	-0.003	-0.005	-0.029	0.005
	(0.026)	(0.026)	(0.025)	(0.032)	(0.028)
Middle School * IHS COVID Deaths (vs KG)	0.006	0.008	0.000	-0.048*	0.012
	(0.026)	(0.026)	(0.026)	(0.029)	(0.029)
High School * IHS COVID Deaths (vs KG)	-0.070**	-0.072**	-0.079***	-0.108***	-0.050
	(0.029)	(0.029)	(0.030)	(0.032)	(0.032)
District FE	X	X	X	X	X
Pre-Pandemic Covariates x Age Group	X	X	X	X	X
F-Statistic	97.2	114.4	102.6	103.8	103.8
N District × Age	36,261	40,062	42,004	35,561	35,561
N Districts	9,328	10,315	10,983	9,121	9,121

Note: * p<0.1, ** p<0.05, *** p<0.01. First column shows the main paper results (from Table S3, column 4). Second column includes additional districts with learning modes from a different source, MCH Strategic Data. Third column removes the restriction that districts have at least 10 students per grade in all years from 2016-2022. Fourth and fifth columns calculate pre-COVID enrollment trends using data from 2012-2020 (rather than 2016-2020). In all models, enrollment weights are the district-age group's total enrollment in the relevant pre-COVID period. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are robust.

Table S10. Sensitivity of Results for 2020-21 Enrollment Deviations by Race/Ethnicity

Outcome: %-Deviation from Enrollment Trend	Main Results	Impute Learning Modes	No Minimum Grade Size	2012-2020 Linear Enrollment Trends	2012-2020 Quadratic Enrollment Trends
White Virtual Mean	**-0.064**	**-0.064**	**-0.061**	**-0.077**	**-0.057**
Black (vs White)	0.051***	0.033**	0.045***	0.077***	0.039**
	(0.016)	(0.014)	(0.016)	(0.018)	(0.018)
Black * In-Person (vs White)	-0.056***	-0.051***	-0.057***	-0.042***	-0.059***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)
Black * Hybrid (vs White)	-0.031***	-0.036***	-0.029***	-0.030***	-0.034***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)
Hispanic (vs White)	0.032**	0.027*	0.038**	0.001	0.055***
	(0.016)	(0.015)	(0.016)	(0.019)	(0.017)
Hispanic * In-Person (vs White)	-0.040***	-0.037***	-0.040***	-0.020***	-0.042***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)
Hispanic * Hybrid (vs White)	-0.026***	-0.027***	-0.026**	-0.016	-0.030***
	(0.009)	(0.008)	(0.010)	(0.012)	(0.008)
Asian (vs White)	0.035**	0.029*	0.032	0.061**	0.017
	(0.018)	(0.017)	(0.021)	(0.025)	(0.019)
Asian * In-Person (vs White)	-0.047***	-0.042***	-0.052***	-0.067***	-0.041***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)
Asian * Hybrid (vs White)	-0.009	-0.011	-0.014	-0.024**	0.001
	(0.009)	(0.008)	(0.010)	(0.010)	(0.009)
Black * IHS COVID Deaths (vs White)	-0.048**	-0.046**	-0.032	0.003	-0.059**
	(0.021)	(0.021)	(0.022)	(0.025)	(0.023)
Hispanic * IHS COVID Deaths (vs White)	-0.050**	-0.053**	-0.040*	-0.060**	-0.064**
	(0.023)	(0.023)	(0.024)	(0.029)	(0.026)
Asian * IHS COVID Deaths (vs White)	-0.072***	-0.070***	-0.074***	-0.133***	-0.049
	(0.027)	(0.027)	(0.027)	(0.033)	(0.030)
District FE	X	X	X	X	X
Pre-Pandemic Covariates x Race/Ethnicity	X	X	X	X	X
F-Statistic	79.2	78.4	83.6	78.7	78.7
N Districts x Race/Ethnicity x Age	48,906	52,137	93,387	45,966	45,966
N Districts	6,876	7,422	10,535	6,443	6,443

Note: * p<0.1, ** p<0.05, *** p<0.01. Regressions include one observation per district-race-age (kindergarten, elementary, middle). First column shows the main paper results (from Table S4, column 4). Second column includes additional districts with learning modes from a different source, MCH Strategic Data. Third column removes the restriction that districts have at least 10 students per grade in all years from 2016-2022. Fourth and fifth columns calculate pre-COVID enrollment trends using data from 2012-2020 (rather than 2016-2020). In all models, enrollment weights are the district-racial/ethnic group's total enrollment in the relevant pre-COVID period. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. We also control for race-specific area poverty rate/household income/adults with a college degree, charter school penetration, and indicators for imputed values of these variables. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are robust.

Table S11. Sensitivity of 2021-22 Learning Mode Results by Race/Ethnicity

Outcome: %-Deviation from Enrollment Trend	2020-21 Model, All Districts	2020-21 Model, 2021-22 Districts	2021-22 Model, No COVID Controls
White Omitted Category Mean	**-0.071**	**-0.056**	**-0.056**
Black (vs White)	0.053**	0.052*	0.006
	(0.024)	(0.028)	(0.018)
Black * 2022 Masks Optional			-0.028**
			(0.012)
Black * 2021 In-Person (vs White)	-0.062***	-0.061***	-0.018**
	(0.010)	(0.011)	(0.009)
Black * 2021 Hybrid (vs White)	-0.052***	-0.049***	-0.016**
	(0.011)	(0.019)	(0.007)
Hispanic (vs White)	0.036	0.081***	0.036*
	(0.023)	(0.026)	(0.019)
Hispanic * 2022 Masks Optional			0.013
			(0.012)
Hispanic * 2021 In-Person (vs White)	-0.041***	-0.050***	-0.033***
	(0.009)	(0.010)	(0.009)
Hispanic * 2021 Hybrid (vs White)	-0.036**	-0.086***	-0.023***
	(0.016)	(0.017)	(0.006)
Asian (vs White)	0.004	0.058*	0.066***
	(0.030)	(0.032)	(0.023)
Asian * 2022 Masks Optional			-0.018
			(0.017)
Asian * 2021 In-Person (vs White)	-0.054***	-0.067***	-0.020*
	(0.012)	(0.012)	(0.011)
Asian * 2021 Hybrid (vs White)	-0.021	-0.073***	-0.027***
	(0.015)	(0.018)	(0.007)
Black * IHS COVID Deaths (vs White)	-0.039	-0.035	
	(0.033)	(0.037)	
Hispanic * IHS COVID Deaths (vs White)	-0.013	0.054	
	(0.040)	(0.044)	
Asian * IHS COVID Deaths (vs White)	-0.141***	-0.057	
	(0.040)	(0.044)	
District FE	X	X	X
Pre-Pandemic Covariates x Race/Ethnicity	X	X	X
F-Statistic	79.2	11.0	17.7
N	48,906	45,182	45,182
N Districts	6,876	5,999	5,999

Note: * p<0.1, ** p<0.05, *** p<0.01. COVID death rates are from June-August 2020 (rather than 2021 in main models). Regressions include one observation per district-race-age (kindergarten, elementary, middle). Omitted category mean is for virtual districts in first column and for masks-required districts in other columns. Pre-pandemic trends are specific to each district-race-age group. Sample includes districts with at least 10 same-age students in two racial/ethnic groups in all years from 2016-2022. Observations are weighted by the district's total enrollment in that race-age group in 2016-2020. Columns 1-2 control for the proportion of county residents who always wear a mask (July 2020) interacted with race/ethnicity. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. We also control for race-specific area poverty rate/household income/adults with a college degree, charter school penetration, and indicators for imputed values of these variables. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S12. 2020-21 Public vs Charter Deviations From Pre-Pandemic Enrollment Trend by Learning Mode and Student Race/Ethnicity

	Public Enrollment		Public + Charter Enrollment	
Outcome: %-Deviation from Enrollment Trend	OLS	IV	OLS	IV
White Virtual Mean	**-0.063**	**-0.063**	**-0.065**	**-0.065**
Black (vs White)	0.007	0.010	0.144*	0.157*
	(0.039)	(0.043)	(0.079)	(0.080)
Black * In-Person (vs White)	-0.039***	-0.049***	-0.042***	-0.071***
	(0.008)	(0.017)	(0.008)	(0.015)
Black * Hybrid (vs White)	-0.027***	-0.026*	-0.038***	-0.044***
	(0.008)	(0.015)	(0.009)	(0.012)
Hispanic (vs White)	-0.003	0.004	0.059	0.070
	(0.036)	(0.037)	(0.058)	(0.058)
Hispanic * In-Person (vs White)	-0.014	-0.025*	-0.016*	-0.030**
	(0.010)	(0.013)	(0.009)	(0.012)
Hispanic * Hybrid (vs White)	-0.019**	-0.024*	-0.018**	-0.020
	(0.009)	(0.014)	(0.009)	(0.012)
Asian (vs White)	-0.026	-0.016	0.073	0.083
	(0.048)	(0.051)	(0.066)	(0.066)
Asian * In-Person (vs White)	-0.017	-0.004	-0.017	-0.012
	(0.013)	(0.022)	(0.014)	(0.022)
Asian * Hybrid (vs White)	0.002	0.029	-0.010	0.008
	(0.014)	(0.018)	(0.013)	(0.017)
Black * IHS COVID Deaths (vs White)	-0.085*	-0.090*	-0.078	-0.095*
	(0.047)	(0.049)	(0.053)	(0.054)
Hispanic * IHS COVID Deaths (vs White)	-0.053	-0.067	-0.096	-0.101
	(0.062)	(0.063)	(0.068)	(0.068)
Asian * IHS COVID Deaths (vs White)	-0.019	0.023	-0.100	-0.069
	(0.090)	(0.090)	(0.083)	(0.082)
District FE	X	X	X	X
Pre-Pandemic Covariates x Race/Ethnicity	X	X	X	X
F-Statistic		20.5		20.6
N Districts × Race/Ethnicity × Age	9,100	9,100	9,100	9,100
N Districts	784	784	784	784

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Regressions include one observation per district-race-age (kindergarten, elementary, middle). In "Public + Charter models" enrollment counts include the public district plus the enrollment of all charters located inside their geographic catchment zone. Pre-pandemic trends are specific to each district-race-age group or district/charter-race-age group. Observations are weighted by the district's (or district's + charter's) total enrollment in that race-age group in 2016-2020. All models control for the proportion of county residents who always wear a mask (July 2020) interacted with race/ethnicity. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship, teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. We also control for race-specific area poverty rate/household income/adults with a college degree, charter school penetration, and indicators for imputed values of these variables. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S13. The Role of Partisanship in Explaining 2020-21 Race/Ethnicity Results

Outcome: %-Deviation from Enrollment Trend	Main Model	No Partisanship Controls	Strong Clinton Districts
White Virtual Mean	**-0.064**	**-0.064**	**-0.061**
Black (vs White)	0.051***	0.061***	0.027
	(0.016)	(0.015)	(0.045)
Black * In-Person (vs White)	-0.056***	-0.052***	-0.054
	(0.007)	(0.006)	(0.042)
Black * Hybrid (vs White)	-0.031***	-0.029***	-0.033***
	(0.006)	(0.006)	(0.012)
Hispanic (vs White)	0.032**	0.042***	0.002
	(0.016)	(0.015)	(0.046)
Hispanic * In-Person (vs White)	-0.040***	-0.035***	-0.025
	(0.006)	(0.006)	(0.038)
Hispanic * Hybrid (vs White)	-0.026***	-0.025***	-0.007
	(0.009)	(0.009)	(0.010)
Asian (vs White)	0.035**	0.039**	-0.039
	(0.018)	(0.018)	(0.050)
Asian * In-Person (vs White)	-0.047***	-0.044***	-0.087**
	(0.008)	(0.007)	(0.041)
Asian * Hybrid (vs White)	-0.009	-0.009	0.018*
	(0.009)	(0.009)	(0.010)
Black * IHS COVID Deaths (vs White)	-0.048**	-0.048**	-0.124***
	(0.021)	(0.020)	(0.043)
Hispanic * IHS COVID Deaths (vs White)	-0.050**	-0.051**	-0.086*
	(0.023)	(0.023)	(0.044)
Asian * IHS COVID Deaths (vs White)	-0.072***	-0.072***	-0.117***
	(0.027)	(0.027)	(0.045)
District FE	X	X	X
Pre-Pandemic Covariates x Race/Ethnicity	X	X	X
F-Statistic	79.2	86.3	1.6
N	48,906	48,906	7,621
N Districts	6,876	6,876	864

Note: * p<0.1, ** p<0.05, *** p<0.01. In "Strong Clinton Districts" more than two-thirds of votes cast in the 2016 presidential election went for Hillary Clinton. Regressions include one observation per district-race-age (kindergarten, elementary, middle). Pre-pandemic trends are specific to each district-race-age group. Sample includes districts with at least 10 same-age students in two racial/ethnic groups in all years from 2016-2022. Observations are weighted by the district's total enrollment in that race-age group in 2016-2020. All models control for the proportion of county residents who always wear a mask (July 2020) interacted with race/ethnicity. Pre-pandemic characteristics are the district's racial/ethnic composition and percent receiving free or reduced price lunch, standardized test scores, racial segregation, 2016 partisanship (in relevant specifications), teacher union strength score, urbanicity, area poverty rate/household income/adults with a college degree, and area enrollment in charter schools. We also control for race-specific area poverty rate/household income/adults with a college degree, charter school penetration, and indicators for imputed values of these variables. IHS = Inverse Hyperbolic Sine, FE = fixed effects. Standard errors are clustered by district.

Table S14. Descriptive Statistics by Learning Mode, Public School Districts in Analytic Sample

	All Districts	Districts with Learning Mode Data	Districts in 2021 Age Models	Districts in 2022 Age Models	Districts in 2021 Race Models	Districts in 2022 Race Models
COVID-19 Environment						
Deaths/1,000 (monthly)	0.081	0.083	0.082	0.085	0.084	0.086
	(0.074)	(0.075)	(0.075)	(0.074)	(0.075)	(0.074)
County Mask-Wearing Rate 2020	0.650	0.660	0.658	0.657	0.664	0.661
	(0.138)	(0.132)	(0.132)	(0.130)	(0.128)	(0.127)
County Vaccination Rate 2021	0.483	0.481	0.479	0.490	0.480	0.491
	(0.234)	(0.239)	(0.239)	(0.232)	(0.241)	(0.233)
District Characteristics						
Prop. White	0.505	0.495	0.499	0.498	0.482	0.487
	(0.296)	(0.296)	(0.296)	(0.292)	(0.285)	(0.284)
Prop. Black	0.152	0.153	0.155	0.156	0.161	0.160
	(0.182)	(0.181)	(0.181)	(0.183)	(0.181)	(0.182)
Prop. Hispanic	0.277	0.286	0.282	0.284	0.291	0.289
	(0.247)	(0.250)	(0.250)	(0.252)	(0.246)	(0.248)
Prop. Asian	0.056	0.058	0.056	0.055	0.058	0.056
	(0.086)	(0.087)	(0.084)	(0.084)	(0.085)	(0.084)
Prop. Free Reduced Lunch	0.533	0.536	0.536	0.533	0.535	0.531
	(0.230)	(0.231)	(0.232)	(0.232)	(0.232)	(0.232)
Prop. ELL	0.097	0.099	0.099	0.099	0.101	0.101
	(0.093)	(0.094)	(0.094)	(0.095)	(0.091)	(0.091)
District Mean Test Score	0.001	0.002	0.004	0.003	0.005	0.004
	(0.354)	(0.356)	(0.358)	(0.362)	(0.359)	(0.362)
White-Black Segregation Index (0-1)	0.149	0.152	0.149	0.141	0.153	0.143
	(0.165)	(0.167)	(0.165)	(0.152)	(0.165)	(0.151)
White-Hispanic Segregation Index (0-1)	0.114	0.116	0.113	0.109	0.116	0.111
	(0.125)	(0.126)	(0.123)	(0.116)	(0.124)	(0.116)
Area Characteristics						
2016 Trump Vote Share	0.464	0.456	0.459	0.464	0.451	0.460
	(0.195)	(0.194)	(0.195)	(0.183)	(0.191)	(0.180)
Teacher Union Strength Score (0-4)	1.992	2.011	1.992	1.968	1.979	1.958
	(0.659)	(0.663)	(0.659)	(0.659)	(0.663)	(0.661)
Prop. District Suburban	0.402	0.414	0.413	0.429	0.428	0.440
	(0.404)	(0.406)	(0.408)	(0.407)	(0.408)	(0.406)
Prop. District Town	0.112	0.106	0.107	0.108	0.102	0.104
	(0.270)	(0.263)	(0.266)	(0.266)	(0.259)	(0.260)
Prop. District Rural	0.195	0.188	0.187	0.178	0.162	0.161
	(0.298)	(0.292)	(0.290)	(0.274)	(0.259)	(0.253)
Prop. Adults College Degree	0.311	0.313	0.312	0.313	0.319	0.318
	(0.142)	(0.143)	(0.143)	(0.144)	(0.143)	(0.144)
Poverty Rate	0.136	0.136	0.136	0.136	0.136	0.135
	(0.066)	(0.067)	(0.067)	(0.068)	(0.066)	(0.067)
Median Household Income	59,404	59,837	59,596	59,809	60,189	60,300
	(21,038)	(21,235)	(21,258)	(21,492)	(21396)	(21,584)
Prop. Area Enrollment in Charters	0.042	0.044	0.038	0.039	0.039	0.040

	(0.106)	(0.108)	(0.076)	(0.077)	(0.077)	(0.078)
N Districts	13,038	11,268	9,328	7,255	6,874	5,997
N Students	46,233,489	43,599,378	41,857,085	39,784,398	39,811,020	38,339,850

Note: Statistics are weighted by districts' pre-pandemic total enrollment. District and area characteristics are measured prior to the pandemic. COVID deaths are at the county level and are from March-August 2020. Sample includes regular public districts with learning mode data available in the COVID-19 School Data Hub that enrolled at least 10 students in every grade in every year from 2016-2022. Nearby charter/private schools are schools within 10 miles of the district. Prop. = proportion, ELL = English Language Learner. District test scores are scaled to a standard normal distribution.

Table S15. Predictors of 2020-21 Learning Modes and 2021-22 Mask Policies

Outcome Variable	In-Person	Hybrid	Masks Not Required
Dependent Variable Mean	*0.46*	*0.27*	*0.42*
Enrollment Quintile 2	-0.063***	0.073***	0.023
	(0.015)	(0.014)	(0.033)
Enrollment Quintile 3	-0.106***	0.121***	0.003
	(0.016)	(0.015)	(0.033)
Enrollment Quintile 4	-0.208***	0.166***	-0.059*
	(0.017)	(0.016)	(0.034)
Enrollment Quintile 5	-0.216***	0.109***	-0.075**
	(0.019)	(0.018)	(0.035)
Prop. Black	0.159***	-0.427***	0.241***
	(0.034)	(0.038)	(0.034)
Prop. Hispanic	0.047	-0.127***	0.093**
	(0.032)	(0.031)	(0.038)
Prop. Asian	-0.646***	0.039	-0.925***
	(0.164)	(0.120)	(0.229)
Prop. Free Reduced Lunch	-0.009	-0.050	-0.099
	(0.092)	(0.111)	(0.083)
Prop. ELL	-0.151***	-0.057*	-0.029
	(0.032)	(0.033)	(0.041)
District Mean Test Score	0.092***	-0.007	0.147***
	(0.017)	(0.017)	(0.022)
White-Black Segregation Index (0-1)	-0.070	-0.039	-0.153**
	(0.057)	(0.057)	(0.075)
White-Hispanic Segregation Index (0-1)	-0.031	-0.007	-0.028
	(0.085)	(0.080)	(0.116)
Area Characteristics			
2016 Trump Vote Share 50-75%	0.168***	-0.042***	0.222***
	(0.011)	(0.010)	(0.012)
2016 Trump Vote Share >75%	0.359***	-0.172***	0.339***
	(0.014)	(0.016)	(0.017)
Strong Teacher Unions	-0.221***	0.044***	-0.319***
	(0.008)	(0.008)	(0.008)
Prop. District Suburban	-0.142***	0.126***	-0.064***
	(0.024)	(0.024)	(0.023)
Prop. District Town	-0.079***	0.041	0.007
	(0.025)	(0.026)	(0.024)
Prop. District Rural	-0.121***	0.053**	-0.020
	(0.026)	(0.026)	(0.025)
Above-Median Poverty Rate	-0.035***	0.003	-0.050***
	(0.011)	(0.012)	(0.014)
Above-Median Prop. Adults College Degree	-0.091***	0.043***	-0.082***
	(0.011)	(0.011)	(0.013)
Above-Median Household Income	-0.025**	-0.023*	-0.005
	(0.012)	(0.012)	(0.014)
Prop. Area Enrollment in Charters	-0.108	-0.069	0.144**
	(0.073)	(0.059)	(0.072)
Structural Controls			
SEDA Covariates Imputed: County-Level	-0.101**	0.129***	-0.156*
	(0.039)	(0.034)	(0.091)
Missing Test Scores	0.003	-0.007	-0.053

	(0.019)	(0.021)	(0.045)
Missing County Demographics	2.293***	-1.323***	
	(0.132)	(0.128)	
Missing Partisanship	-1.279***	2.891***	
	(0.117)	(0.175)	
Missing White-Black Segregation	0.028	0.009	0.014
	(0.037)	(0.042)	(0.055)
Missing White-Hispanic Segregation	-0.007	-0.184	0.204*
	(0.105)	(0.121)	(0.114)
N	11,268	11,268	7,643

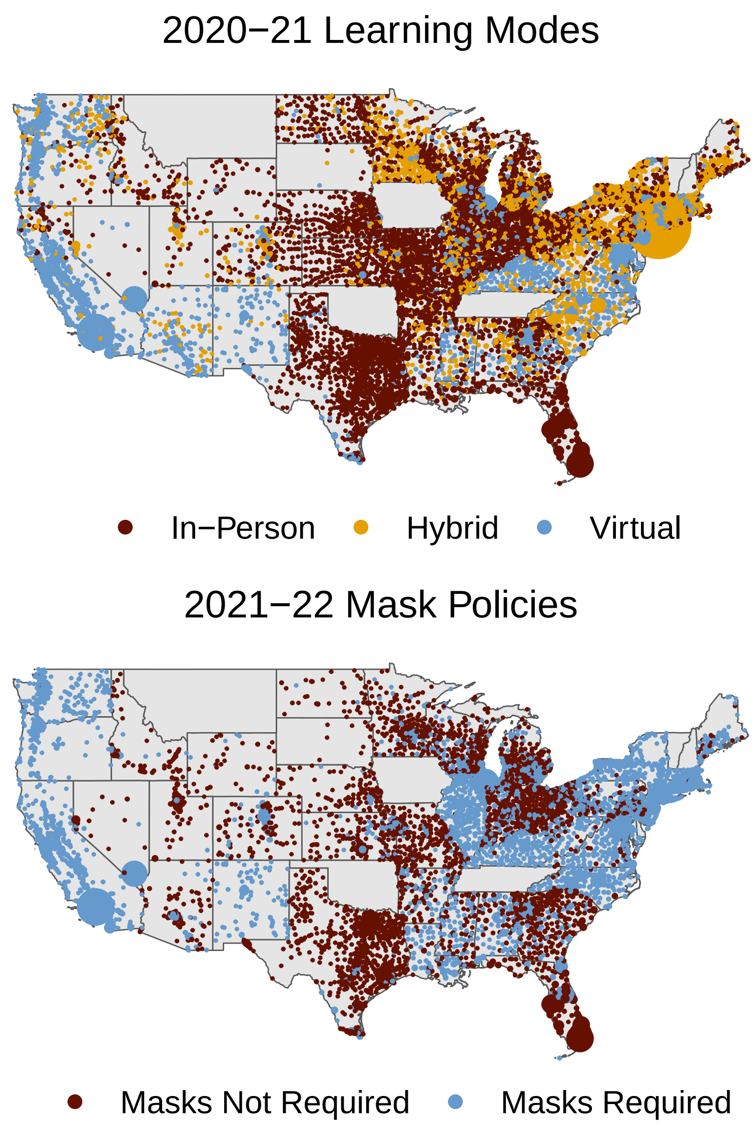
Note: * p<0.1, ** p<0.05, *** p<0.01. Coefficients in columns 1-2 are marginal effects from a multinomial logistic regression (omitted category: virtual district), evaluated at sample means. Coefficients in column 3 are marginal effects from a binomial logistic regression (omitted category: masks required), evaluated at sample means. Strong Teacher Union = Fordham index score ≥2.5 (score ranges from 0-4). Prop. = proportion, ELL = English Language Learner, SEDA = Stanford Education Data Archive (data source for a subset of Area Characteristics). Sample includes public school districts with non-imputed start mode data. Standard errors are robust.

Table S16. First Stages From Instrumental Variables Models, District Total Enrollment

	Start In-Person	Start Hybrid	Masks Not Required
Predicted Prob. In-Person	0.354***	0.242***	
	(0.061)	(0.058)	
State LOO In-Person	0.641***	0.113***	
	(0.080)	(0.022)	
Prob. In-Person * State LOO	0.370**	-0.278***	
	(0.151)	(0.070)	
Predicted Prob. Hybrid	-0.055	0.067	
	(0.095)	(0.062)	
State LOO Hybrid	-0.208***	0.441***	
	(0.060)	(0.081)	
Prob. Hybrid * State LOO	0.221	1.253***	
	(0.178)	(0.200)	
Predicted Prob. No Masks Required			0.058
			(0.041)
State LOO No Masks Required			0.418***
			(0.085)
Prob. No Masks Required * State LOO			0.873***
			(0.122)
Inv. Hyperb. Sine COVID Deaths per 1,000, Mar-Aug	0.065	-0.040	-0.233
	(0.101)	(0.103)	(0.298)
Prop. Always Wear Mask, Jul 2020	0.109	-0.183***	
	(0.083)	(0.069)	
Prop. Vaccinated, Aug 2020			0.013
			(0.095)
Constant	-0.065	0.034	-0.061
	(0.064)	(0.051)	(0.061)
R-Squared	0.546	0.361	0.537
F-Statistic	552.5	209.6	237.3
N	9,328	9,328	7,255

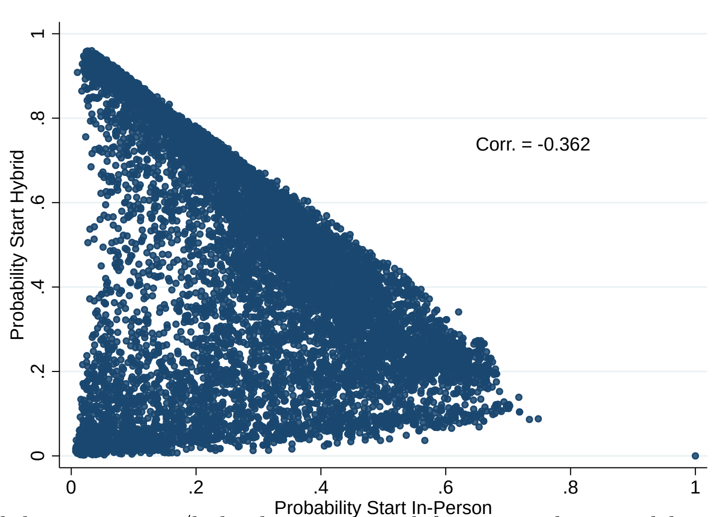
Note: * p<0.1, ** p<0.05, *** p<0.01. F-stats are Sanderson-Widmeijer, which partial out the other endogenous regressor. District Predicted Prob. In-Person/Hybrid is the predicted probability of in-person/hybrid start to the 2020-21 school year (relative to virtual) based on district observable pre-pandemic characteristics, estimated using a multinomial logit. Predicted Prob. No Masks Required is the predicted probability of no mask requirement to start to the 2021-22 school year based on district observable pre-pandemic characteristics, estimated using a binomial logit. LOO = leave-one-out (the proportion of other districts in the state starting in-person/hybrid or with no masks required), Prop. = proportion. Sample excludes districts with fewer than 10 students in any grade in any year from 2016-2022. Regressions are weighted by the district's total enrollment in 2016-2020. Standard errors are robust.

Figure S1. Geographic Variation in District COVID Policies



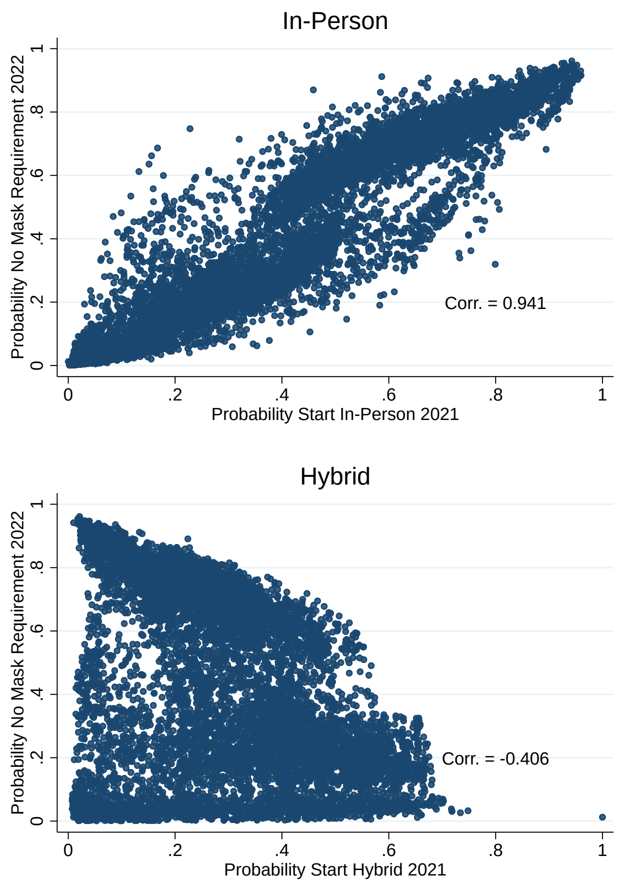
Note: Learning mode data come from the COVID School Data Hub (CSDH), mask policy data come from the Return to Learn (R2L) Tracker. Marker size is scaled to district 2019-20 enrollment.

Figure S2. Correlation of In-Person and Hybrid Predicted Probabilities



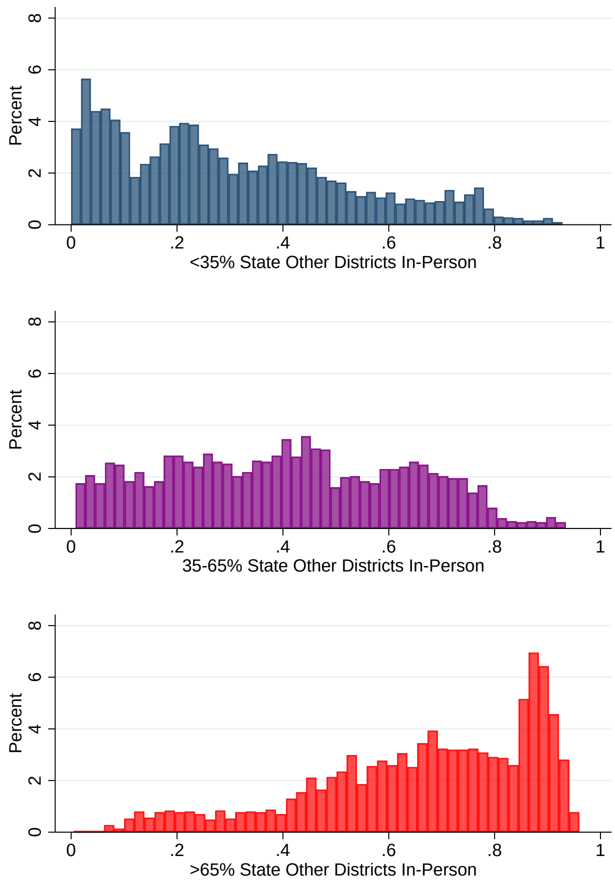
Note: Predicted probability in-person/hybrid is estimated from a multinomial logistic regression of 2020-21 learning modes on pre-pandemic observable characteristics. See Table S15 for coefficients underlying predictions.

Figure S3. Correlation of In-Person and Hybrid with Masking Predicted Probabilities



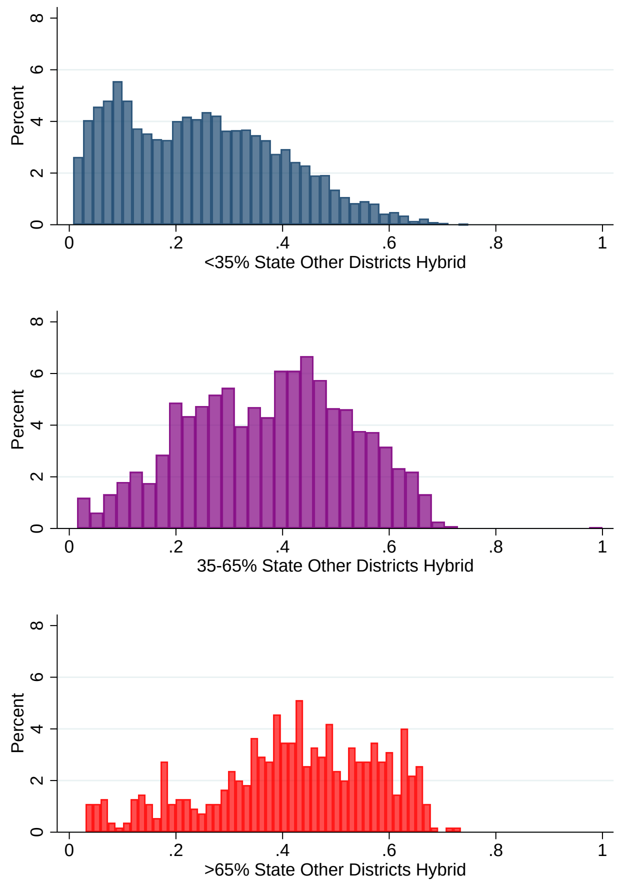
Note: Predicted probability in-person/hybrid is estimated from a multinomial logistic regression of 2020-21 learning modes on pre-pandemic observable characteristics. Predicted probability for no masks required is estimated using a binomial logistic regression. See Table S15 for coefficients underlying predictions.

Figure S4. Distribution and Correlation of Instruments for In-Person Learning



Note: N=3,950 (top panel), 2,432 (middle), 2,782 (bottom). Predicted probability in-person is estimated from a multinomial logistic regression of 2020-21 learning modes on pre-pandemic observable characteristics. See Table S15 for coefficients underlying predictions. Proportion of other districts in a state who started in-person acts as a leave-one-out estimator for state policy variation.

Figure S5. Distribution and Correlation of Instruments for Hybrid Learning



Note: N=6,462 (top panel), 2,205 (middle), 497 (bottom). Predicted probability hybrid is estimated from a multinomial logistic regression of 2020-21 learning modes on pre-pandemic observable characteristics. See Table S15 for coefficients underlying predictions. Proportion of other districts in a state who started hybrid acts as a leave-one-out estimator for state policy variation.