Manuscript deliverable: School district policy guidance as a tool for mitigating the spread of COVID-19

# Abstract

Schools are a critical environment for children, youth, families, and communities. Emerging research suggests the effectiveness of COVID-19 mitigation strategies to allow for safe in-person attendance. Districts’ guidance of mitigation strategies, however, has received very little attention, an important gap given their role in establishing universal policies and practices. The purpose of this study was to assess the association between districts’ COVID-19 prevention policies, aligned with the Centers for Disease Control and Prevention’s public school operational guidance from 2021, and subsequent COVID-19 case counts in schools during the 2021-2022 school year? Overall, we find evidence that a layered approach to prevention in the form of five mitigation strategies, including upkeep of HVAC systems, requiring physical distancing, encouraging that students stay home when sick, requiring quarantining, and offering screening and testing for students, was associated with a smaller increase in case rates between the fall and spring. These findings support prior research demonstrating a link between layered prevention policies and COVID-19 mitigation, and demonstrate the importance of school districts in translating guidance to practice on the school level.

# Introduction

Safe schools are essential to the healthy development of children and youth, a foundational context providing services beyond education, including food and nutritional support, after-school programming, and multidisciplinary health care services extending to families and communities (Verlenden et al. 2021). Due to the school environment’s indelible position in the social context, strategies intended to address public health emergencies must be tailored to minimize disruption of services while also effectively addressing potential emergency events. The onset of the COVID-19 pandemic led to school closures and an abrupt shift to virtual educational models, eliminating many of the benefits to in-person attendance (Zimmerman, Jackman, and Benjamin 2022). Moreover, school-based closures disproportionately affected children of low-income families and widened disparities in achievement by socioeconomic status as well as digital access among Black and Latinx communities [Kuhfeld et al. (2020)](Nicola et al. 2020)(Oster et al. 2021). In addition, families of children with underlying health conditions, physical or developmental disabilities, or neurodivergent learning differences struggled to get the necessary support and accommodations (Cernich, Lee, and Bianchi 2022). Among other costs, parents and caregivers suffered from emotional distress and worried about job security and teachers contemplated retirement in mass [Verlenden et al. (2021)](Zimmerman, Jackman, and Benjamin 2022)[Gillani et al. (2022)](Lambert, Trott, and Baugh 2020).

The Centers for Disease Control and Prevention (CDC) published operational guidance for in-person learning (Honein, Barrios, and Brooks 2021). While these recommendations were modified as researchers better understood effective methods to mitigating COVID-19 in communities and schools, overall a layered approach to prevention has endured to include multiple recommendations, such as recommending and/or requiring any of universal masking, physical distancing, students staying home when sick, quarantining for those exposed to COVID-19, contact tracing, improving cleaning practices, screening and testing for students, and improving air quality via filtration methods, such as HEPA filters and HVAC systems (Honein, Barrios, and Brooks 2021). Emerging research suggests the effectiveness of these individual and layered approaches to mitigating the spread of COVID-19 in schools, though there is less information regarding school districts’ role in implementation.

School districts are an important governing body in determining the curricula schools offer and distribution of federal funding across schools. School districts also play a role in implementation of health-promoting policies (e.g.(Li et al. 2022)), and during the pandemic many published their COVID-19 mitigation strategies for the public to follow (Honein, Barrios, and Brooks 2021). However, to our knowledge there has not been any research evaluating whether these guidance materials are followed by schools to the extent that COVID-19 spread is mitigated. Therefore, the purpose of this study was to assess the following research question: what is the association between districts’ COVID-19 prevention policies and subsequent COVID-19 case counts in schools? School districts are an important determinant of school practices, and as such may be an important facilitator of federal guidance. Understanding the extent to which district guidance may influence cases could help improve public health emergency preparedness and response capabilities.

# Methods

## Data

This research utilizes district policy guidance and school-level COVID-19 case counts collected as part of the National School COVID-19 Prevention Study (NSCPS), funded by the Centers for Disease Control and Prevention (CDC)[[1]](#footnote-1). The NSCPS is a nationally representative stratified random sample of 1,602 K-12 public schools across 1,286 districts, drawn to better understand schools’ response to the pandemic through the 2021-2022 school year and associated outcomes, including the extent to which prevention strategies were effective in mitigating the spread of COVID-19 among students. As part of the NSCPS, publicly-posted district-level COVID-19 prevention policy and reopening guidance documents for sample schools were scraped from district websites and analyzed to identify prevention strategies that were recommended or required of schools. In addition, health departments representing all 50 states and the District of Columbia were contacted and invited to provide available school-level COVID-19 case count data for the 2021-2022 school year.

## Measures

**Outcome of interest**: The outcome of interest was the difference between schools’ spring and fall monthly average COVID-19 case counts, characterized as the average of schools’ monthly number of cases per 100 students across January, February, and March 2022 minus the average of October, November, and December 2021 monthly cases per 100 students. This outcome is hereafter referred to as ‘change in case rate.’ For this analytic approach, the key predictors of interest consisted of 10 dichotomous indicators of districts’ COVID-19 prevention strategy guidance for schools that were aligned to represent adherence to CDC’s operational guidance for K-12 schools published prior to July 9, 2021 [Disease Control and Prevention (n.d.)]. To score prevention policy guidance, human raters met to standardize how to categorize and rate strategy implementation requirements using a 41-item scoring rubric assessing the extent to which school district guidance documents required or recommended implementation of the 10 key COVID-19 prevention strategies. Once the raters agreed on the requirements and scoring criteria, they reviewed the policies and recorded their ratings. Criteria for scoring were also used to train a machine learning algorithm that was used to assess and score guidance documents. Prevention strategies were considered “in place” if included in guidance documents. Operational definitions of prevention strategy indicators, as well as covariates, are presented in Table 1. A full description of methods used in the policy assessment can be found in Chapter 2. Methodology Mitigation Outcome Study District Policy Assessment, Appendix A. District Policy Scoring Information and Appendix A1. Background on Automated Document Processing Pipeline Architecture.

Table 1: Study measures

| Measure | Definition |
| --- | --- |
| Vaccination offered | Offered vaccines at district-sponsored events to teachers and staff and/or students. |
| Universal masking requirement | Teachers, staff, and students required to wear masks consistently and correctly (i.e., covering the mouth and nose) at school. |
| Physical distancing | Required that students maintain at least 3 feet of physical distance between each other indoors. |
| Screening testing for students | Offered screening testing of students on a regular basis. |
| Staying home when sick | Encouraged or required that students stay home when sick or tested positive for COVID-19. |
| Contact tracing | Encouraged or recommended that schools conduct contact tracing. |
| Quarantining | Required students to quarantine if identified to be a close contact. |
| Cleaning | Required schools to clean high touch surfaces at least once a day or between uses. |
| HEPA filters | Encouraged use of high-efficiency particulate air (HEPA) filters. |
| HVAC systems | Encouraged replacing, upgrading, maintaining, or inspecting HVAC systems. |
| Cumulative strategy index | Sum of strategies having marginal association with change in case rates (calculation further described below). |
| School-level characteristics | These measures were derived from the National Center for Education Statistics (NCES) for the 2020-2021 school year, and when possible, missing values were filled with estimates from the 2019-2020 school year. See next section for description of approach to ameliorate potential of issues with respect to multicolinearity. |
| Percent student body eligible for free and reduced lunch | The percent of the schools' students who were eligible or free and reduced lunch |
| School locale | City, Rural, Suburb, Town |
| Study enrollment composition | Percent of student body Asian, American Indian or Alaska Native, Black/African American, Hispanic/Latino, Native Hawaiian or other Pacific Islander, Not specific, Two or more races, and White (each race/ethnicity represented individually) |
| County-level characteristics |  |
| Social Vulnerability Index (SVI) | Overall summary index indicating the relative vulnerability of U.S. Census tracts across four themes: socioeconomic, household composition & disability, minority status & language, and housing type & transportation. Drawn from the…. |
| Change in county COVID-19 case rates | Difference in average of 7-day rolling average for the 15th of each month case rate per 100,000 people between October - December and January - March, corresponding with the time period used for calculating school case rate changes. Pulled from HHS Protect |
| Region | Midwest, Northeast, South, West |
| State | 20 states |

## Analyses

In total, policy guidance documents were collected from 1,184 of 1,286 (92%) of school districts comprising the schools in the total sample, with 28 of the 51 health departments (55%) reporting on 641 schools (40% of total sample). Schools without at least one month of case reporting during the spring and fall periods were removed, resulting in an eligible sample of 347 schools (22% of total sample) across 338 districts (26% of districts) and 20 states (39% of states and DC).

All analyses were conducted using R version 4.2.1 and included testing for outliers, identified as any observation in which the change in case rate is outside 3.5 standard deviations from the mean (R Core Team 2022). Descriptive statistics for all study variables were computed, as well as t-tests of mean differences between groups defined by the presence (inclusion) of prevention strategies within guidance documents, and Pearson’s correlation coefficient between changes in school-level COVID-19 case rates and continuous covariates following standardization (Disease Control et al., n.d.). Finally, intra-class correlation coefficients (ICC) were calculated to test for clustering of outcomes by region, state, and district. For modeling results, 95% confidence intervals and p-values are displayed, with a significance threshold of and marginal significance indicated by p-value .

Following the descriptive analysis, the modeling sequence consisted of two stages. First, a Random Forest (RF) algorithm was developed for identifying the most predictive covariates among the school-level variables (student population composition, free lunch eligible, etc.), and completing this process over 100 iterations (Strobl et al. 2008). RF algorithms can be used to rank variables based on their predictive association with the outcome of interest, and due to limited sample size for the current study as well as expected collinear relationships between school race/ethnicity proportions, we elected to utilize a data-driven approach for a priori excluding covariates with the least predictive value (Breiman 2001). For the current study, covariates with positive variable importance for greater than 50% of the 100 iterations were retained for the modeling stage.

The second stage of analysis was comprised of three sets of multilevel models, all accounting for nesting of schools within state, nested within region (Finch, Bolin, and Kelley 2019). First, individual multilevel models with one strategy and important covariates as predictors were estimated to assess each strategy’s association with the change in case rates before inclusion of other strategies; second, estimation of a full model including all strategies for relative comparison; and third a set of models to compare schools having multiple strategies in place, characterized by cumulative indices. The cumulative indices were calculated as the sum of strategies identified from the first set of models using p-value cutoffs of 0.1 and 0.2, with additional testing of indices calculated using cutoffs of 0.5, 0.7, and all strategies provided in the appendix. These cumulative indices were estimated in separate models and compared using Akaike information criterion (AIC) and Bayesian information criterion (BIC) for selection of the best cumulative index (Finch, Bolin, and Kelley 2019).

# Results

Five schools had changes in case rates greater than 3.5 standard deviations from the mean and were subsequently removed from the data for these analyses, resulting in an initial sample of 342 schools. Table 1 provides summary statistics for this sample. Three hundred forty-two schools had case data available for fall 2021 and spring 2022, with an overall average of 1.16 (SD = 1.87) more cases per 100 students per month during spring 2022 than fall 2021. Notably, none of the school-level covariates or county-level predictors were significantly associated with changes in case rates, suggested by lack of correlation (last column). ICCs indicated significant clustering by region (ICC = 0.08) and state (0.22), though not by district (0.00). Therefore, accounting for clustering of schools by region and state was necessary for the modeling stage. Overall, the final sample consisted of 55 schools from the Midwest (16%), 94 from the Northeast (27%), 120 from the South (35%), and 73 from the West (21%). Schools were comparatively distributed by locale, including city (24%), rural (27%), suburb (35%), and town (14%). For region and locale, table X displays minimum, maximum, mean, and standard deviation of case rates.

Table 2: Summary statistics of changes in case rates and standardized covariates

| Construct | n (min, max) | Mean (SD) | Correlation (p-value) |
| --- | --- | --- | --- |
| Change in school COVID-19 case rate | 342 (-6.25, 7.81) | 1.16 (1.87) |  |
| Change in county COVID-19 case rate | 342 (-13.67, 14747.43) | 826.27 (2375.13) | 0.004 (0.937) |
| Percent American Indian/Alaska Native | 338 (0, 98.7) | 1.64 (9.21) | -0.046 (0.401) |
| Percent Asian | 338 (0, 56) | 4.04 (7.73) | 0.017 (0.754) |
| Percent Black or African American | 338 (0, 99.5) | 13.31 (21.69) | 0.038 (0.489) |
| Percent Hispanic or Latino | 338 (0, 100) | 24.97 (26.59) | 0.066 (0.229) |
| Percent Native Hawaiian or other Pacific Islander | 338 (0, 9.7) | 0.24 (0.7) | -0.041 (0.453) |
| Percent no race specified | 338 (0, 2.6) | 0.02 (0.17) | -0.047 (0.386) |
| Percent two or more races | 338 (0, 23.8) | 3.86 (3.09) | -0.004 (0.936) |
| Percent White | 338 (0, 100) | 51.92 (32) | -0.07 (0.202) |
| Percent free and reduced lunch | 331 (0.4, 100) | 51.31 (28.3) | 0.027 (0.63) |
| SVI Overall Rank | 342 (0, 99.94) | 51.31 (27.83) | 0.068 (0.21) |
| Midwest | 55 (-2.87, 4) | 0.43 (1.33) |  |
| Northeast | 94 (-2.93, 7.67) | 1.47 (2.02) |  |
| South | 120 (-6.25, 7.5) | 1.68 (2.06) |  |
| West | 73 (-1.16, 7.81) | 0.46 (1.24) |  |
| City | 83 (-2.6, 6.74) | 1.06 (1.78) |  |
| Rural | 92 (-6.25, 7.5) | 1.17 (2) |  |
| Suburb | 119 (-2.93, 7.81) | 1.3 (1.93) |  |
| Town | 48 (-2.87, 5.17) | 0.97 (1.65) |  |
| Region |  |  |  |
| Locale |  |  |  |

Table 2 reviews summary statistics and t-test results for the 10 prevention strategies with changes in case rates as the outcome variable. *No policy* reflects the change in case rate among schools that did not have guidance related to prevention strategy implementation in fall 2021, whereas *Has policy* indicates the change in case rate among schools that had policy guidance for prevention strategies. *Difference in means* provides the mean difference between groups, calculated by subtracting the policy from the no policy mean. Strategies were associated with smaller increases in case rates between semesters, though significant differences were only detected for upkeep of HVAC systems (mean difference = 0.48; p-value = 0.02) and a marginally significant difference for physical distancing (mean difference = 0.38; p-value = 0.08). That is, on average schools with an upkeep of HVAC systems district policy (or guidance) experienced an increase in case rates that was 0.48 per 100 students less than schools without policy guidance. Likewise, schools with a physical distancing guidance had an increase that was 0.38 cases per 100 students less than comparison schools.

Table 2: Summary statistics and t-test results of COVID-19 mitigation strategies

| Construct | n (min, max) | Overall mean (SD) | No policy | Has policy | Difference in means (p-value) |
| --- | --- | --- | --- | --- | --- |
| Vaccination offered | 342 (0, 1) | 0.12 (0.32) | 1.19 | 0.91 | 0.283 (0.276) |
| Universal masking requirements | 342 (0, 1) | 0.26 (0.44) | 1.22 | 1.00 | 0.22 (0.358) |
| Physical distancing | 342 (0, 1) | 0.26 (0.44) | 1.26 | 0.88 | 0.383 (0.08) |
| Screening and testing for students | 342 (0, 1) | 0.15 (0.35) | 1.19 | 0.96 | 0.236 (0.454) |
| Staying home when sick | 342 (0, 1) | 0.41 (0.49) | 1.26 | 1.02 | 0.24 (0.244) |
| Contact tracing | 342 (0, 1) | 0.3 (0.46) | 1.22 | 1.03 | 0.184 (0.383) |
| Quarantining | 342 (0, 1) | 0.32 (0.47) | 1.24 | 1.00 | 0.239 (0.27) |
| Cleaning | 342 (0, 1) | 0.25 (0.44) | 1.15 | 1.19 | -0.035 (0.875) |
| HEPA filters | 342 (0, 1) | 0.04 (0.21) | 1.18 | 0.80 | 0.375 (0.4) |
| HVAC systems | 342 (0, 1) | 0.33 (0.47) | 1.32 | 0.84 | 0.476 (0.019) |

Table three shows results from the first set of multilevel models that were run individually for each strategy. School-level covariates are suppressed for reporting, but those selected for the modeling stage include percent student body Asian, percent student body Black or African American, percent student body two or more races, percent student body White, percent student body free and reduced lunch, school level, and county-level indicators including change in COVID-19 case count rate and SVI Overall Rank. As shown in table three, none of the strategies were statistically significant when covariates were included in models, though three demonstrated a marginal association (p-value < 0.10), including physical distancing (coefficient = -0.38; p-value = 0.07), staying home when sick (-0.33; 0.08), and upkeep of HVAC systems (-0.38; 0.06). In addition, two strategies, offering screening and testing for students (-0.35; 0.18) and requiring quarantining (-0.29; 0.14) had p-values less than 0.20. As such, these strategies were selected for calculation of the cumulative indices, and are reviewed below in table five.

Table 3: Results of multilevel models for each individual strategy accounting

| Strategy | Coefficient (95% interval) | p-value |
| --- | --- | --- |
| Vaccination offered | -0.08 (-0.69, 0.53) | 0.79 |
| Universal masking requirements | -0.13 (-0.54, 0.27) | 0.56 |
| Physical distancinga | -0.38 (-0.83, 0.03) | 0.07 |
| Screening and testing for studentsb | -0.35 (-0.84, 0.2) | 0.18 |
| Staying home when sicka | -0.33 (-0.71, 0.03) | 0.08 |
| Contact tracing | -0.17 (-0.54, 0.22) | 0.41 |
| Quarantiningb | -0.29 (-0.72, 0.08) | 0.14 |
| Cleaning | -0.09 (-0.53, 0.31) | 0.67 |
| HEPA filters | 0.03 (-0.98, 0.96) | 0.95 |
| HVAC systemsa | -0.38 (-0.78, 0.02) | 0.06 |
| aincluded in 3-strategy index;bincluded in 5-strategy index;a;b;a; | | |

Table four shows multilevel model results from including all strategies as predictors in one model. Overall, none of the strategies were significantly associated with changes in case rates. However, percent of student body two or more races was associated with increased changes in case rates (0.24; 95% CI = 0.04 - 0.46).

Table 4: Results of multilevel model including all strategies

| Strategy | Coefficient (95% interval) | p-value |
| --- | --- | --- |
| Intercept | 1.04 (0.32, 1.78) | 0.06 |
| Vaccination offered | 0.33 (-0.44, 1.1) | 0.34 |
| Universal masking requirements | 0.14 (-0.35, 0.68) | 0.60 |
| Physical distancing | -0.28 (-0.84, 0.3) | 0.32 |
| Screening and testing for students | -0.31 (-0.99, 0.36) | 0.32 |
| Staying home when sick | -0.2 (-0.85, 0.47) | 0.54 |
| Contact tracing | 0.13 (-0.42, 0.69) | 0.64 |
| Quarantining | -0.06 (-0.7, 0.56) | 0.86 |
| Cleaning | 0.33 (-0.23, 0.82) | 0.24 |
| HEPA filters | 0.25 (-0.6, 1.29) | 0.62 |
| HVAC systems | -0.4 (-1.01, 0.17) | 0.19 |
| Percent two or more races | 0.24 (0.04, 0.46) | 0.03 |
| Percent Asian | 0.01 (-0.21, 0.23) | 0.94 |
| Percent White | -0.15 (-0.5, 0.26) | 0.42 |
| Percent free and reduced lunch | -0.25 (-0.57, 0.1) | 0.13 |
| SVI Overall Rank | 0.04 (-0.2, 0.28) | 0.76 |
| Percent Black or African American | -0.07 (-0.35, 0.18) | 0.59 |
| High school | 0.31 (-0.15, 0.8) | 0.21 |
| Middle school | 0.27 (-0.19, 0.72) | 0.25 |
| Change in county COVID-19 case rate | -0.08 (-0.45, 0.3) | 0.62 |

Results from the multilevel models with the cumulative indices as the predictors of interest are depicted in table X. The first set of results correspond with the cumulative index calculated using strategies having a marginal association with case rates (p-value < 0.10; three strategies) and the second with the sum of strategies that had p-values < 0.20 (five total). Both indices were treated as ranked ordinal, with a minimum of zero (baseline). Finally, a third column of results are presented to further explore differences between the two cumulative indices.

Schools located in districts with prevention guidance on all three strategies, including physical distancing, staying home when sick, and upkeep of HVAC systems, had a significantly smaller increase in case rates between fall and spring (-0.53; -1.02 - -0.05). When offering screening and testing for students and requiring student quarantining were added to the cumulative index, in districts with prevention guidance on all five strategies had a significantly decreased change in case rates (-0.84; -1.58 - -0.03). Using AIC and BIC to compare model fit, the cumulative index with five strategies had the smallest AIC but marginally higher BIC. Therefore, to further compare the cumulative indices for selection of the best combination, we developed mutually exclusive indicators for having all three or all five strategies. These results are presented in the last column of table X. Having the first three strategies was no longer statistically significant (-0.32;-0.87, 0.26), but the indicator for having all five strategies was significantly associated with a smaller change in case rate (-0.93; -1.69, -0.11), estimates which are comparable to those presented in the second column. These results further suggest that successful COVID-19 mitigation was driven by the presence of five strategies, rather than three, and as such, the models utilizing five-category indicators were selected as best.

Table 5: Results of multilevel model with cumulative index of marginally significant strategies

| Cumulative number strategies | 0.1\_Coefficient (95% CI) | 0.1\_p-value | 0.2\_Coefficient (95% CI) | 0.2\_p-value | final\_Coefficient (95% CI) | final\_p-value |
| --- | --- | --- | --- | --- | --- | --- |
| 1 | 0.15 (-0.38, 0.69) | 0.6 | 1.06 (0.34, 1.84) | 0 |  |  |
| 2 | -0.23 (-0.79, 0.33) | 0.39 | -0.2 (-0.82, 0.37) | 0.52 |  |  |
| 3 | -0.53 (-1.06, 0) | 0.04 | -0.12 (-0.65, 0.43) | 0.68 | -0.32 (-0.87, 0.26) | 0.26 |
| 4 |  |  | -0.24 (-0.79, 0.32) | 0.41 |  |  |
| 5 |  |  | -0.84 (-1.57, -0.09) | 0.03 | -0.93 (-1.69, -0.11) | 0.02 |
| aic | 1312.563 |  | 1305.808 |  |  |  |
| bic | 1373.397 |  | 1374.246 |  |  |  |

# Summary

This study provides evidence that district-level guidance on COVID-19 prevention can help schools reduce the spread of COVID-19. Specifically, we found that districts providing prevention guidance on three strategies, encouraging upkeep of HVAC systems, requiring physical distancing, and encouraging that students stay home when sick, marginally attenuate COVID-19 spread. However, there is stronger evidence suggesting the effect of combining or layering five strategies, including upkeep of HVAC systems, requiring physical distancing, encouraging that students stay home when sick, requiring quarantining, and offering screening and testing for students, indicated by a statistically significant association between changes in COVID-19 case rates and the cumulative index. The five-strategy indicator also had a stronger association with change case rates when compared with the three-strategy indicator. As such, these results offer a number of key takeaways to inform ongoing efforts to promote more equitable and safe school environments in the context of current and future public health emergencies.

First, as suggested by a growing body of literature, the spread of airborne disease among children and adolescents attending public schools can be mitigated, which is particularly noteworthy given the concern over consequences to remote-only learning (e.g., learning loss, breaking social ties) (Engzell, Frey, and Verhagen 2021). While it is still unclear the extent to which individual strategies rank in importance and contribute to reduced spread, it appears that COVID-19 mitigation is achieved in schools when districts develop policies and/or provide prevention guidance and communicate that schools should utilize a combination of multiple prevention strategies. Furthermore, these results hold after accounting for nesting of schools within state and region, underscoring the generalizability of the strategies against heterogeneous contexts.

Second, district-level COVID-19 prevention strategy requirements and recommendations served as a proxy for strategy implementation in schools. Although we do not fully understand schools’ implementation fidelity or additional strategies that schools may have employed on their own, these results demonstrate the influence of school districts to effectively provide guidance to schools. As such, there is an opportunity for federal and state public health agencies to further improve schools’ implementation of mitigation strategies by tailoring guidance for districts to understand and disseminate to their constituents as best as possible (Li et al. 2022). Indeed, our results may also reflect that districts with stronger ties to schools as well as greater communication capabilities were more effective in translating CDC guidance to attainable strategies by schools.

Third, the lack of responsiveness from the majority of state health departments as well the limited availability of school-level case data, may indicate an opportunity for improving infrastructure in preparation for future emergencies. Only 28 of 51 (55%) health departments were responsive to our request for data, and of these health departments, only 20 had data usable for the current analysis. While it is clear that many health departments were simply too overwhelmed to accommodate our request, others were hesitant for a variety of reasons. Therefore, there is an opportunity for federal agencies to build stronger relationships with states/local health departments in order to improve surveillance systems and the public’s overall trust in them, reducing schools’ and communities’ vulnerabilities to public health crises.

## Limitations

There are several limitations to consider in the context of the current study that should be considered for future research. First, sample size significantly limited our ability to detect smaller effects resulting from strategy implementation. The low sample size may have been due in part to the resources needed to conduct a study of this magnitude, but it may have also been influenced by hesitation of health departments to collaborate. We were only able to cull usable data for approximately 22% of study schools. As such, there is likely response bias (e.g., well-resourced districts may have been more likely to post policy guidance, and schools in these districts may also have had greater potential for collecting case data) due to health department self-selection to participate and share available data. Furthermore, since health departments collected data from schools without a unified approach, we cannot rule out that our results may be reflective of disparate COVID-19 data collection methods. For instance, it is unclear whether schools were able to distinguish between student cases occurring as a result of in-person attendance or from outside contexts (e.g., social gatherings). In order to conduct more robust research and evaluation with respect to public health response and intervention in the school context, it is essential that rigorous and transparent surveillance systems be built in partnership with states, health departments, districts, and schools.

Second, from a modeling perspective the relatively high number of recommended strategies introduced the potential for reporting spurious associations. For example, actively selecting which strategies to include in cumulative indices is subject to researchers’ discretion and therefore the potential for cherry-picking results remains. The current study attempted to address this possibility by using a Random Forest approach for selecting the most important covariates to be included in modeling. Additionally, rather than relying on a “throw in the kitchen sink” approach to analyzing the strategies of interest, a priori approach was used to assess inclusion of individual prevention strategies within district-level guidance and then to develop cumulative indices from those meeting particular thresholds of association with the outcome (p-values < 0.10 and < 0.20, see appendix for additional tests). Despite these efforts to objectively evaluate prevention strategies, it remains essential that future research be conducted to critique our findings. For example, the appendix shows results from cumulative indices calculated using thresholds of 0.5, 0.6, 0.7, 0.8, and all strategies. While the cumulative index from the 0.5 cutoff had a significant association for those employing all six strategies, the other cumulative indices did not reach statistical significance. With this limitation in mind, schools in districts with guidance on all five strategies had a reduced change in case rates, suggesting the importance of taking a layered approach to prevention. Future research should further study the benefits to layered prevention approaches to further identify important combinations of strategies, as well as addressing issues associated with limits to availability of data. For example, exploring non-parametric methods may yield additional insights, particularly in the context of outliers (Whitaker et al. 2020). Using the current methodology, we removed five observations that were greater than 3.5 standard deviations from the mean. Including these observations in the sample resulted in models where none of the strategies, cumulative index, or covariates were statistically significant.

Third, internet retrieval of publicly available district-level policies for inclusion of COVID-19 prevention guidance can be an imprecise and resource intensive process subject to error. For instance, our scraping of district websites was limited to the timing that policies were updated, as data were scraped during the fall of 2021, and policies may have been updated before and/or thereafter. To address this limitation for the current study, we assessed updates to district guidance and their potential association with cases in spring 2022. Overall, better incorporation of time will potentially lead to more precise results, as well as adoption of technologies and methods more prominent in other fields (e.g., machine learning methods).

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## Appendix

Results of multilevel models with cumulative indices of thresholds 0.5, .06, 0.7, 0.8, and 1

| Cumulative number strategies | 0.5\_Coefficient (95% CI) | 0.5\_p-value | 0.6\_Coefficient (95% CI) | 0.6\_p-value | 0.7\_Coefficient (95% CI) | 0.7\_p-value | 0.8\_Coefficient (95% CI) | 0.8\_p-value | 1\_Coefficient (95% CI) | 1\_p-value |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1 | 1.28 (0.37, 2.04) | 0 | 1.22 (0.27, 1.98) | 0.01 | 1.23 (0.31, 2.14) | 0.01 | 1.25 (0.22, 2.16) | 0.01 | 1.16 (0.13, 2.09) | 0.03 |
| 2 | -0.04 (-0.69, 0.66) | 0.92 | -0.07 (-0.9, 0.74) | 0.86 | -0.26 (-1.08, 0.62) | 0.53 | 0.01 (-0.86, 0.82) | 0.98 | 0.13 (-0.62, 0.94) | 0.75 |
| 3 | -0.22 (-0.75, 0.33) | 0.45 | 0.12 (-0.5, 0.74) | 0.71 | 0.01 (-0.77, 0.67) | 0.99 | -0.26 (-1.01, 0.4) | 0.49 | -0.24 (-1.02, 0.46) | 0.53 |
| 4 | -0.28 (-0.89, 0.31) | 0.37 | -0.25 (-0.79, 0.37) | 0.41 | 0.1 (-0.52, 0.74) | 0.76 | 0.46 (-0.39, 1.14) | 0.24 | 0.46 (-0.38, 1.33) | 0.24 |
| 5 | -0.1 (-0.74, 0.55) | 0.77 | -0.19 (-0.88, 0.53) | 0.6 | -0.26 (-0.9, 0.39) | 0.44 | -0.26 (-0.92, 0.32) | 0.38 | -0.19 (-0.86, 0.37) | 0.55 |
| 6 | -0.93 (-1.69, -0.09) | 0.03 | -0.4 (-1.11, 0.29) | 0.26 | -0.38 (-1.08, 0.29) | 0.27 | -0.67 (-1.41, 0.02) | 0.06 | -0.72 (-1.37, 0) | 0.05 |
| 7 |  |  | -0.76 (-1.87, 0.34) | 0.15 | -0.21 (-1.08, 0.75) | 0.64 | 0.23 (-0.56, 1.05) | 0.57 | -0.12 (-0.87, 0.65) | 0.75 |
| 8 |  |  |  |  | -0.78 (-1.83, 0.31) | 0.14 | -0.82 (-1.75, 0.11) | 0.09 | -0.41 (-1.23, 0.54) | 0.35 |
| 9 |  |  |  |  |  |  | -0.4 (-2.24, 1.33) | 0.68 | -0.46 (-2.43, 1.48) | 0.63 |

## References

Breiman, Leo. 2001. “Random Forests.” *Machine Learning* 45 (1): 5–32.

Cernich, Alison N., Sonia Lee, and Diana W. Bianchi. 2022. “Building the Evidence for Safe Return to School During the COVID-19 Pandemic.” *Pediatrics* 149 (Supplement\_2). <https://doi.org/10.1542/peds.2021-054268b>.

Disease Control, Centers for, and Prevention. n.d. “Operational Guidance for k-12 Schools and Early Care and Education Programs to Support Safe in-Person Learning.” [https://www.cdc.gov/coronavirus/2019-ncov/community/schools-childcare/k-12-childcare-guidance.html#](https://www.cdc.gov/coronavirus/2019-ncov/community/schools-childcare/k-12-childcare-guidance.html).

Disease Control, Centers for, Prevention/ Agency for Toxic Substances, Disease Registry/ Geospatial Research Analysis, and Services Program. n.d. “CDC/ATSDR Social Vulnerability Index 2020 Database US.” <https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html>.

Engzell, Per, Arun Frey, and Mark D. Verhagen. 2021. “Learning Loss Due to School Closures During the COVID-19 Pandemic.” *Proceedings of the National Academy of Sciences* 118 (17). <https://doi.org/10.1073/pnas.2022376118>.

Finch, W Holmes, Jocelyn E Bolin, and Ken Kelley. 2019. *Multilevel Modeling Using r*. CRC Press.

Gillani, Amreen, Rhodri Dierst-Davies, Sarah Lee, Leah Robin, Jingjing Li, Rebecca Glover-Kudon, Kayilan Baker, and Alaina Whitton. 2022. “Teachers’ Dissatisfaction During the COVID-19 Pandemic: Factors Contributing to a Desire to Leave the Profession.” *Frontiers in Psychology* 13 (September). <https://doi.org/10.3389/fpsyg.2022.940718>.

Honein, Margaret A., Lisa C. Barrios, and John T. Brooks. 2021. “Data and Policy to Guide Opening Schools Safely to Limit the Spread of SARS-CoV-2 Infection.” *JAMA* 325 (9): 823. <https://doi.org/10.1001/jama.2021.0374>.

Kuhfeld, Megan, James Soland, Beth Tarasawa, Angela Johnson, Erik Ruzek, and Jing Liu. 2020. “Projecting the Potential Impact of COVID-19 School Closures on Academic Achievement.” *Educational Researcher* 49 (8): 549–65. <https://doi.org/10.3102/0013189x20965918>.

Lambert, Juli Anna, Kim Trott, and Reginald F. Baugh. 2020. “An Analysis of K-12 School Reopening and Its’ Impact on Teachers.” *Journal of Primary Care & Community Health* 11 (January): 215013272096750. <https://doi.org/10.1177/2150132720967503>.

Li, Jingjing, Zach Timpe, Nicolas Suarez, Carmen L. Ashley, Catherine N. Rasberry, and Leah Robin. 2022. “Intervening at the Right Level to Improve Student Health: An Analysis of Levels of Influence on Sexual Behavior of High School Students.” *AIDS Education and Prevention* 34 (4): 300–310. <https://doi.org/10.1521/aeap.2022.34.4.300>.

Nicola, Maria, Zaid Alsafi, Catrin Sohrabi, Ahmed Kerwan, Ahmed Al-Jabir, Christos Iosifidis, Maliha Agha, and Riaz Agha. 2020. “The Socio-Economic Implications of the Coronavirus Pandemic (COVID-19): A Review.” *International Journal of Surgery* 78 (June): 185–93. <https://doi.org/10.1016/j.ijsu.2020.04.018>.

Oster, Emily, Rebecca Jack, Clare Halloran, John Schoof, Diana McLeod, Haisheng Yang, Julie Roche, and Dennis Roche. 2021. “Disparities in Learning Mode Access Among k12 Students During the COVID-19 Pandemic, by Race/Ethnicity, Geography, and Grade Level United States, September 2020april 2021.” *MMWR. Morbidity and Mortality Weekly Report* 70 (26): 953–58. <https://doi.org/10.15585/mmwr.mm7026e2>.

R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.

Strobl, Carolin, Anne-Laure Boulesteix, Thomas Kneib, Thomas Augustin, and Achim Zeileis. 2008. “Conditional Variable Importance for Random Forests.” *BMC Bioinformatics* 9 (1). <https://doi.org/10.1186/1471-2105-9-307>.

Verlenden, Jorge V., Sanjana Pampati, Catherine N. Rasberry, Nicole Liddon, Marci Hertz, Greta Kilmer, Melissa Heim Viox, et al. 2021. “Association of Children’s Mode of School Instruction with Child and Parent Experiences and Well-Being During the COVID-19 Pandemic COVID Experiences Survey, United States, October 8november 13, 2020.” *MMWR. Morbidity and Mortality Weekly Report* 70 (11): 369–76. <https://doi.org/10.15585/mmwr.mm7011a1>.

Whitaker, Rebecca Garr, Nina Sperber, Michael Baumgartner, Alrik Thiem, Deborah Cragun, Laura Damschroder, Edward J. Miech, Alecia Slade, and Sarah Birken. 2020. “Coincidence Analysis: A New Method for Causal Inference in Implementation Science.” *Implementation Science* 15 (1). <https://doi.org/10.1186/s13012-020-01070-3>.

Zimmerman, Kanecia O., Jennifer G. Jackman, and Daniel K. Benjamin. 2022. “From Research to Policy: Reopening K12 Schools in North Carolina During the COVID-19 Pandemic.” *Pediatrics* 149 (Supplement\_2). <https://doi.org/10.1542/peds.2021-054268e>.

1. <https://www.cdc.gov/healthyyouth/data/nscps/index.htm> [↑](#footnote-ref-1)