Deliverable Submission, December 15, 2022

Draft Manuscript of Peer-Reviewed Publication, Deliverable 9.5

Centers for Disease Control and Prevention

Evaluating School Strategies for COVID-19 Mitigation



|  |  |  |
| --- | --- | --- |
| **Submitted to:**  Centers for Disease Control and Prevention Division of Adolescent and School Health National Center for HIV/AIDS, Viral Hepatitis, STD, and TB Prevention  1600 Clifton Road, MS E-75  Atlanta, GA 30329 | **Submitted by:**  ICF Incorporated, L.L.C. 9300 Lee Highway  Fairfax, VA 22031 | **Contract #**  GS00F010CA  **Task order #**  75D301-21-F-10577 |

Icon

Description automatically generated

*Formatted for Submission to: Journal to be determined*

**School district policy guidance as a tool for mitigating the spread of COVID-19**

Zach Timpe1, Luke McConnell1, Ronaldo Iachan1, Catherine Rasberry2, Colleen Murray1, Sanjana Pampati2, [additional ICF/CDC authors]

**Author affiliations:** 1 ICF, Atlanta, GA; 2 Centers for Disease Control and Prevention, Division of Adolescent and School Health, Atlanta, GA

**Funding:** Funding for this study was provided through contract delivery order #75D30121F10577 from the Center for Disease Control and Prevention’s Division of Adolescent and School Health to ICF.

**Conflicting Interests:** The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Disclaimer:** The findings and conclusions in the article are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

**Acknowledgements:** This study was funded, in part, by task order 75D30121F10577 from the Centers for Disease Control and Prevention to ICF. We acknowledge the contributions of the school staff participants, as well as Sarah Conklin, James Demery, Cherrelle Dorleans, Brandee Hicks, Adrian King, Erica McCoy, Leah Powell, Lynnea Roberts, India Rose, April Carswell, Syreeta Skelton-Wilson; Carmen Ashley, Lorin Boyce, Nancy Brener, Michelle Carman-McClanahan, Xiaoyi Deng, Neha Kanade Cramer, Dana Keener Mast, Catherine Lesesne, Seraphine Pitt Barnes, Leah Robin, Lucas Godoy Garraza, Nicole Gonzalez, Christine Walrath, and the rest of the National School COVID-19 Prevention Study team.

**School district policy guidance as a tool for mitigating the spread of COVID-19**

**Abstract**

Students in the United States have been severely affected by the COVID-19 pandemic. Schools serve as a critical environment for children, youth, families, and communities. Emerging research suggests the effectiveness of COVID-19 mitigation strategies, allowing schools to reopen and operate safely. Districts’ guidance of COVID-19 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 Operational Guidance for K-12 Schools, and subsequent COVID-19 case counts in schools during the 2021-2022 school year. Data analysis were conducted sing survey data from a stratified random sample of 1,602 K-12 public schools across 1,286 school districts and publicly available district-level COVID-19 guidance (e.g., policies, reopening plans, prevention guidance). Overall findings indicate 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, quarantining, and offering screening and testing for students, was associated with a smaller increase in COVID-19 case rates between the fall and spring. These findings align with previous research that found the effectiveness of layering and promoting the implementation of multiple COVID-19 mitigation strategies in schools.

Keywords: COVID-19, school districts, mitigation strategies, policy, COVID case data

**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, & 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, & Bianchi 2022). Among other costs, parents and caregivers suffered from emotional distress and worried about job security and teachers contemplated retirement in mass (Gillani et al, 2022; Lambert, Trott, & Baugh, 2020; Verlenden et al., 2021; Zimmerman, Jackman, & Benjamin 2022)

The Centers for Disease Control and Prevention (CDC) published operational guidance for in-person learning (Honein, Barrios, & 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, & 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 (Li et al., 2022), and during the pandemic many published their COVID-19 mitigation strategies for the public to follow (Honein, Barrios, & 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 school district COVID-19 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). The National School COVID-19 Prevention Study (NSCPS) was initiated to better understand the implementation and effectiveness of infection prevention strategies in K-12 school settings. NSCPS is a population-based, longitudinal study designed to be representative of K-12 public schools in the United States. The study used a stratified random sample of 1,602 K-12 public schools across 1,286 school districts with strata defined by region (Northeast, South, Midwest, West), school level (elementary, middle, high), and NCES locale (city, town, suburb, rural). The comprehensive sampling frame of K-12 public schools for NSCPS was based on the National Center for Education Statistics (NCES)’s Common Core of Data (CCD) for public schools, and enriched with data files obtained from MDR Inc. (Market Data Retrieval, Inc.) The MDR data files contained school information including enrollments, grades, race distributions within the school, district, and county, and other contact information for schools across the nation.

The cohort of schools was followed for four waves of data collection from October 2021 through May 2022 to better understand schools’ response to the pandemic during 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 available district-level COVID-19 guidance (e.g., policies, reopening plans, prevention guidance) were retrieved from district websites and analyzed to identify prevention strategies that were required or recommended at the district-level. 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 sample schools (N=1,602) for the 2021-2022 school year.

**Measures**

For this analysis, the dependent variable was defined as 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.”

Predictors of interest consisted of 10 dichotomous indicators of districts’ COVID-19 prevention strategy guidance that were aligned to represent adherence to CDC’s operational guidance for K-12 schools published on July 9, 2021 (CDC, 2021).

Policy guidance was scored using a combination of human scoring and machine learning (ML) methods. Human raters met to standardize how to categorize and rate COVID-19 prevention guidance using a 41-item scoring rubric assessing the extent to which school district guidance documents required or recommended implementation of 10 key COVID-19 prevention strategies (Table 1). Once raters agreed on the requirements and scoring criteria, they reviewed 427 guidance documents containing image files and infographics and recorded their scores. Criteria for scoring were also used to train a keyword matching model machine learning algorithm that was used to assess and score 757 guidance documents in pdf and Microsoft Word format.

As a proxy for school-level prevention strategy implementation, prevention strategies were considered “in place” if scored as adhering to federal operational guidance for K-12 schools. Operational definitions of prevention strategy indicators, as well as school-level and county-level covariates, are presented in Table 1.

Table 1: Study measures

| Measure | Definition |
| --- | --- |
| *COVID-19 Prevention Strategies* |  |
| 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 characteristics1* |  |
|  |  |
| Percent student body eligible for free and reduced lunch | The percent of the schools' students who were eligible for 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 American Community Survey (ACS) of the U.S. Census Bureau |
| 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 |

## 1 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.

**Data Analyses**

In total, policy guidance documents were collected from 1,184 of 1,286 (92%) of school districts comprising the schools from the NSCPS total sample, with 28 of the 51 health departments (55%) which accounted for 641 schools (40% of total sample). Schools without at least one month of case reporting during fall 2021 and spring 2022 were removed, resulting in an eligible analytic sample of 347 schools (22% of total sample) across 338 districts (26% of districts containing schools in total sample) 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 of prevention strategy guidance (inclusion/adherence to federal guidance) and Pearson’s correlation coefficient between changes in school-level COVID-19 case rates and continuous covariates following standardization. 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 for over 100 iterations (Strobl et al., 2008). RF algorithms can be used to rank variables based on their predictive association with an outcome of interest. Due to the 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). Covariates with positive variable importance for greater than 50% of the 100 iterations were retained for the modeling stage.

The second stage of analysis included three sets of multilevel models, all accounting for nesting of schools within state, nested within region (Finch, Bolin, & Kelley, 2019). To begin, individual multilevel models were constructed 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; next, estimation of a full model was created including all strategies for relative comparison; and then a third set of models were built 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, & 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 a 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 (ICC = 0.22), though not by district (ICC = 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 2 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) |
| **Region** |  |  |  |
| 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) |  |
| **Locale** |  |  |  |
| 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) |  |
|  |  |  |  |

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 without district guidance on prevention strategy implementation in fall 2021, whereas *Has policy* indicates the change in case rate among schools that had district guidance on prevention strategy implementation. *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, although significant differences were only detected for upkeep of HVAC systems (mean difference = 0.48; p = 0.02) and a marginally significant difference for physical distancing (mean difference = 0.38; p = 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 district-level guidance on HVAC systems. 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 prevention 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 3 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 for covariatesa

| 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 distancingb | -0.38 (-0.83, 0.03) | 0.07 |
| Screening and testing for studentsc | -0.35 (-0.84, 0.2) | 0.18 |
| Staying home when sickb | -0.33 (-0.71, 0.03) | 0.08 |
| Contact tracing | -0.17 (-0.54, 0.22) | 0.41 |
| Quarantiningc | -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 systemsb | -0.38 (-0.78, 0.02) | 0.06 |
| a Full list of covariates can be found in Table 2.  b included in 3-strategy index; c included in 5-strategy index | | |

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 5. The first set of results correspond with the cumulative index calculated using strategies having a marginal association with case rates (p < 0.10; three strategies) and the second corresponds with the sum of strategies that had p < 0.20 (five strategies). Both indices were treated as ranked ordinal, with a minimum of zero (none of the specific strategies implemented). Finally, a third column (comparison) 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 2021 and spring 2022 (-0.53; -1.06 – 0.00). When offering screening and testing for students and requiring student quarantining were added to the cumulative index, districts with prevention guidance on all five strategies had a significantly decreased change in case rates (-0.84; -1.57 – -0.09). 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 5. 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 are presented in the second column. These results suggest that the effects of COVID-19 prevention efforts were driven by the presence of layering 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 | Coefficient (95% CI) | p-value | Coefficient (95% CI) | p-value | Coefficient (95% CI) | p-value |
| --- | --- | --- | --- | --- | --- | --- |
| Cutoff | 0.1 | | 0.2 | | Comparison | |
| 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, 0.00) | 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 |  |  |  |

**Discussion**

This study provides evidence that district-level guidance on COVID-19 prevention may help schools reduce the spread of COVID-19. Specifically, we found that districts providing prevention guidance on three strategies, upkeep (encouraging replacing, upgrading, maintaining, or inspecting) of HVAC systems, requiring physical distancing, and encouraging that students stay home when sick, marginally attenuated 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 in case rates when compared with the three-strategy indicator. As such, these results offer several considerations 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 prevented, which is particularly noteworthy given the concern over consequences to remote-only learning (e.g., learning loss, breaking social ties) (Engzell, Frey, & 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 prevention is achieved in schools when districts develop policies and/or provide prevention guidance and communicate that schools should utilize a combination of prevention strategies, even after accounting for nesting of schools within state and region, underscoring the generalizability of prevention strategy implementation.

Second, district-level COVID-19 prevention 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’ capacity by tailoring guidance for districts to share with schools (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 recommended federal guidance to attainable strategy implementation by schools.

Third, the lack of responsiveness from most 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 likely that many health departments were simply too overwhelmed to accommodate our request, others may have been hesitant to provide data. As such federal agencies should seek to build stronger relationships with states/local health departments to improve surveillance systems and build trust.

## Limitations

There are several limitations to consider in the context of the current study that should be considered for future research. Sample size significantly limited our ability to detect smaller effects. We were only able to cull usable school-level COVID-19 case data from health departments 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 and reporting to health departments) 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 because of in-person attendance or from outside contexts (e.g., social gatherings). To conduct more robust research and evaluation with respect to public health emergency response and intervention in the school context, it is essential that rigorous and transparent surveillance systems be built in collaboration with states, health departments, districts, and schools.

Internet retrieval of publicly available district-level 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 guidance documents were updated, as data were scraped during the fall of 2021, and guidance may have been updated before or after this time. To address this limitation for the current study, we assessed the date district guidance documents were created or last updated and their potential association with cases in spring 2022.

In addition, 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 biased 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. 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 the impact of prevention strategy guidance and implantation, it remains essential that future research be conducted to explore these associations further. While the cumulative index from the 0.5 cutoff had a significant association among schools employing all six strategies, the other cumulative indices did not reach statistical significance (see Appendix). With this limitation in mind, schools in districts with prevention 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 investigate 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.

**Conclusion**

Despite these limitations, this study provides a baseline understanding of the impact district policy and prevention guidance can have on COVID-19 prevention. Layering COVID-19 prevention strategies, in combination with district-level guidance, was associated with a smaller increased change in COVID-19 case rates. This study provides evidence and support for improving school districts capacity to develop clear policies to improve schools’ public health emergency preparedness and response capabilities.

## Appendix

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

| Number strategies | Coefficient (95% CI) | p-value | Coefficient (95% CI) | p-value | Coefficient (95% CI) | p-value | Coefficient  (95% CI) | p-value | Coefficient  (95% CI) | p-value |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Index cutoffs |  | 0.5 |  | 0.6 |  | 0.7 |  | 0.8 |  | 1 |
| 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, L. (2001). Random Forests. *Machine Learning*, 45 (1): 5–32.

Cernich, A. N., Lee, S., & Bianchi, D. W. (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>.

Centers for Disease Control and Prevention. (2021). “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).

Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program. CDC/ATSDR Social Vulnerability Index 2020. Database US. <https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html>. Accessed on November 15, 2022.

Engzell, P., Frey, A., & Verhagen, M. D. (2021). Learning loss due to school closures during the COVID-19 pandemic. *Proceedings of the National Academy of Sciences*, *118*(17), e2022376118. <https://doi.org/10.1073/pnas.2022376118>.

Finch, W. H., Bolin, J. E., & Kelley, K. (2019). *Multilevel modeling using R*. Crc Press.

Gillani, A., Dierst-Davies, R., Lee, S., Robin, L., Li, J., Glover-Kudon, R., ... & Whitton, A. (2022). Teachers’ dissatisfaction during the COVID-19 pandemic: Factors contributing to a desire to leave the profession. *Frontiers in Psychology*, *13*. <https://doi.org/10.3389/fpsyg.2022.940718>.

Honein, M. A., Barrios, L. C., & Brooks, J. T. (2021). Data and policy to guide opening schools safely to limit the spread of SARS-CoV-2 infection. *Jama*, *325*(9), 823-824. <https://doi.org/10.1001/jama.2021.0374>.

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the potential impact of COVID-19 school closures on academic achievement. *Educational Researcher*, *49*(8), 549-565. <https://doi.org/10.3102/0013189x20965918>.

Lambert, J. A., Trott, K., & Baugh, R. F. (2020). An Analysis of K-12 School Reopening and Its’ Impact on Teachers. *Journal of Primary Care & Community Health*, *11*, 2150132720967503.<https://doi.org/10.1177/2150132720967503>.

Li, J., Timpe, Z., Suarez, N., Ashley, C. L., Rasberry, C. N., & Robin, L. (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, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., ... & Agha, R. (2020). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International Journal of Surgery*, *78*, 185-193. <https://doi.org/10.1016/j.ijsu.2020.04.018>.

Oster, E., Jack, R., Halloran, C., Schoof, J., McLeod, D., Yang, H., ... & Roche, D. (2021). Disparities in learning mode access among K–12 students during the COVID-19 pandemic, by race/ethnicity, geography, and grade level—United States, September 2020–April 2021. *Morbidity and Mortality Weekly Report*, *70*(26), 953. <https://doi.org/10.15585/mmwr.mm7026e2>.

R Core Team. (2013). R: A language and environment for statistical computing. <https://www.R-project.org/>.

Strobl, C., Boulesteix, A. L., Kneib, T., Augustin, T., & Zeileis, A. (2008). Conditional variable importance for random forests. *BMC bioinformatics*, *9*(1), 1-11. <https://doi.org/10.1186/1471-2105-9-307>.

Verlenden, J. V., Pampati, S., Rasberry, C. N., Liddon, N., Hertz, M., Kilmer, G., ... & Ethier, K. A. (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 8–November 13, 2020. *Morbidity and Mortality Weekly Report*, *70*(11), 369. <https://doi.org/10.15585/mmwr.mm7011a1>.

Whitaker, R. G., Sperber, N., Baumgartner, M., Thiem, A., Cragun, D., Damschroder, L., ... & Birken, S. (2020). Coincidence analysis: a new method for causal inference in implementation science. *Implementation Science*, *15*(1), 1-10. <https://doi.org/10.1186/s13012-020-01070-3>.

Zimmerman, K. O., Jackman, J. G., & Benjamin, D. K. (2022). From research to policy: Reopening K–12 schools in North Carolina during the COVID-19 pandemic. *Pediatrics*, *149*(Supplement\_2). <https://doi.org/10.1542/peds.2021-054268e>.