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

# Introduction

The purpose of this analysis is to study the effectiveness of school districts’ COVID-19 prevention strategies in mitigating the spread of COVID-19 among school-aged children and adolescents.

As such, the primary research question is, what is the association between districts’ COVID-19 prevention policies and subsequent COVID-19 caseloads in schools?

# 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). 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 consist of 10 dichotomous indicators of COVID-19 prevention strategy implementation that were aligned to represetn adherance to CDC’s operational guidance for K-12 schools. [ADD FURTHER DESCRIPTION OF CDC GUIDANCE AND HOW WE ALIGNED WITH IT]. Prevention strategies were considered “in place” if included in guidance documents obtained from district websites during the fall of 2021. Operational definitions of prevention strategy indicators, as well as covariates, are presented in Table 1. Once school district-level COVID-19 prevention guidance documents were obtained, human raters met to standardize how to categorize and rate strategy implementation requirements. 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 the ML algorithm that was used to assess and score guidance documents. A full description of methods used in the policy assessment can be found XXX.

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 (p-value < .10) association with change in case rates. |
| 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 dropped, 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. The analysis begins by testing for outliers, identified as any observation in which the change in case rate is outside 3.5 standard deviations from the mean. Descriptive statistics for all study variables are reported, 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. Finally, intra-class correlation coefficients (ICC) are 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 consists of two stages. First, developing a Random Forest (RF) algorithm 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. 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. 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 is comprised of three sets of multilevel models, all accounting for nesting of schools within state, nested within region. First, individual multilevel models with one strategy and important covariates as predictors are 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 are calculated as the sum of strategies identified from the first set of models using p-value cutoffs of .1, .2, and .5. These cumulative indices are estimated in separate models, and compared using Akaike information criterion (AIC) and Bayesian information criterion (BIC) for selection of the best cumulative index.

# 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 = .08) and state (.22), though not by district (.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 HVAC systems (mean difference = .48; p-value = .02) and a marginally significant difference for physical distancing (mean difference = .38; p-value = .08). That is, on average schools with a HVAC systems district policy (or guidance) experienced an increase in case rates that was .48 per 100 students less than schools without policy guidance. Likewise, schools with a physical distancing policy in place had an increase that was .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 are included in models, though three demonstrated a marginal association (p-value < .10), including physical distancing (coefficient = -.38; p-value = .07), staying home when sick (-.33; .08), and HVAC systems (-.38; .06). In addition, two strategies, screening and testing for students (-.35; .18) and quarantining (-.29; .14) had p-values less than .20. Finally, contact tracing (-.17; .41) had a p-value less than .50. 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 distancing | -0.38 (-0.83, 0.03) | 0.07 |
| Screening and testing for students | -0.35 (-0.84, 0.2) | 0.18 |
| Staying home when sick | -0.33 (-0.71, 0.03) | 0.08 |
| Contact tracing | -0.17 (-0.54, 0.22) | 0.41 |
| Quarantining | -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 systems | -0.38 (-0.78, 0.02) | 0.06 |

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 (.24; 95% CI = .04 - .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 from the multilevel models including 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 < .10; three strategies), the second with the sum of strategies that had p-values < .20 (five total), and the last set of columns corresponds with the cumulative index calculated using strategies with p-values less than .5 (six total). Given that three, five, and six strategies were selected for inclusion in the sum scores, the indices were treated as ranked ordinal, with a minimum of zero (baseline).

Schools with all three strategies in place, including physical distancing, staying home when sick, and HVAC systems, had a significantly smaller increase in case rates between fall and spring (-.53; -1.07 - -.05). When screening and testing for students and quarantining were added to the cumulative index, schools having all five strategies in place had a significantly reduced change in case rates (-.84; -1.58 - -.03), and schools with only one strategy had a significant increase in the case rate (1.06; 0.3 - 1.85). Finally, when adding the sixth strategy, contact tracing, to the cumulative index, once again schools with all strategies in place had a significantly smaller change in case rates (-.93; -1.74 - -.04), and schools with only one strategy in place had a significantly higher change in cases compared with schools having none of the strategies (1.28; 0.33 - 2.19). Using AIC and BIC to compare model fit, the cumulative index with five strategies had the smallest AIC but larger BIC. Chi-square tests comparing these models yielded a significant chi-squared statistic, indicating that the five-category index had better model fit. As such, this model was 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 | 0.5\_Coefficient (95% CI) | 0.5\_p-value |
| --- | --- | --- | --- | --- | --- | --- |
| 1 | 0.15 (-0.39, 0.71) | 0.6 | 1.06 (0.3, 1.85) | 0 | 1.28 (0.33, 2.19) | 0 |
| 2 | -0.23 (-0.76, 0.27) | 0.39 | -0.2 (-0.8, 0.36) | 0.52 | -0.04 (-0.73, 0.68) | 0.92 |
| 3 | -0.53 (-1.02, 0.05) | 0.04 | -0.12 (-0.66, 0.43) | 0.68 | -0.22 (-0.8, 0.31) | 0.45 |
| 4 |  |  | -0.24 (-0.86, 0.31) | 0.41 | -0.28 (-0.84, 0.28) | 0.37 |
| 5 |  |  | -0.84 (-1.58, -0.03) | 0.03 | -0.1 (-0.76, 0.54) | 0.77 |
| 6 |  |  |  |  | -0.93 (-1.74, -0.04) | 0.03 |
| aic | 1312.563 |  | 1305.808 |  | 1308.856 |  |
| bic | 1373.397 |  | 1374.246 |  | 1381.096 |  |
| pr\_chisq |  |  | 0.005 |  | 1 |  |

# Summary

This study provides evidence that publicly available district-level guidance on COVID-19 prevention can help schools reduce the spread of COVID-19. Specifically, we found that districts’ communication and inclusion of three key strategies within their guidance documents, including HVAC systems, physical distancing, and staying home when sick, marginally attenuate COVID-19 spread. However, there is stronger evidence suggesting the effect of combining or layering of five strategies, including HVAC systems, physical distancing, staying home when sick, quarantining, and screening and testing for students, indicated by a statistically significant association between changes in COVID-19 case rates and the cumulative index. Schools residing in districts with guidance requiring physical distancing, having students stay home when sick, having students quarantine when exposed to COVID-19, offer screening and testing for students, and HVAC systems during fall 2021 had a significantly reduced increase in case rates as compared to schools without guidance on any of the strategies. Additionally, having policy guidance on only one of the strategies was associated with a significantly higher increase in case rates, whereas having less than 100% of the five prevention strategies in policy guidance was not associated with any change. 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). 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 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, which underscore the differences in students’ experiences of the pandemic through a broad environmental backdrop.

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. Indeed, our results may also reflect that reduced COVID-19 spread is a result of transparent and effective relationships between districts and their 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 HDs, only 20 had data usable for the current analysis. While it is likely that some HDs were simply too overwhelmed to accommodate our request, others were clearly uninterested in collaborating. It is essential to overall public health that secure, transparent, and relevant data be available to communities and schools. If stronger relationships between federal agencies and states/local health departments are not built to improve surveillance systems and the public’s overall trust in them, then schools and communities will remain overly vulnerable to public health crises, and future interventions are likely to remain limited in effectiveness as well.

## 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, even after being connected via CDC personnel. Overall, 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 district may have been more likely to be able 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. In order to conduct more robust research and evaluation with respect to public health responses and interventions in the school context, it is essential that better relationships be built with states, local education agencies, and communities writ-large so as to build transparent and trustful partnerships, which should lead to improved buy-in as well as robust data collection and dissemination.

Next, the relatively large number of strategies recommended by the CDC towards mitigating COVID-19 spread made it hard to objectively develop measures from district websites as well as to select relevant covariates without overspecification. The current study attempted to address the potential issues with both limitations by using an RF approach for selecting the most important covariates to be included in modeling. In addition, rather than a “throw in the kitchen sink” approach to analyzing the strategies of interest (even though we do present these results for sake of completeness), we decided a priori to assess them individually and then to develop cumulative indices from those meeting particular thresholds of association with the outcome (p-values < .10, < .20, and < .50). Comparing the cumulative models yielded a surprising result that schools with only one strategy in place tended to experience increased case rates. Alternatively, schools with all strategies in place had a reduced change, suggesting the importance of taking a layered approach to prevention. That is, it takes more than one strategy to mitigate the spread of COVID-19. As a means of checking the sensitivity of the results to the cumulative index we also developed cumulative indices using p-values of .6, and then all 10 strategies. In these cases, none of the cumulative indices were statistically significant. The field may benefit from further study of layered approaches to prevention to further identify important combinations of strategies. Alternatively, exploring non-parametric methods may yield additional insights, particularly in the context of outliers. 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, nor covariates were statistically significant. However, one challenge with non-parametric approaches will be to ensure that results are translated into understandable and actionable recommendations.

Third, scraping and scoring district websites for policies is an imprecise process subject to error and the resources required to complete such as task. For instance, our scraping of district websites was subject to the timing that policies were updated, as data were scraped during the fall of 2021, and policies may have been updated thereafter. Moreover, we used machine learning methods to score publicly-posted policy data, which illustrates the benefits to adopting new technologies and methods, yet better incorporation of time (e.g., more months, using weekly data) will potentially lead to more precise results. To address this limitation for the current study, we assessed updates to district guidance and their potential association with cases in spring 2022. Future research can benefit from better incorporating advanced data processing and scoring mechanisms, rather than relying on people to carry out these processes.