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 guidance documents from district websites were scraped 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 any available COVID-19 case count data for the 2021-2022 school year that had been collected from schools comprising the sample.

## Measures

**Outcome of interest**: The outcome of interest is the difference between schools’ spring and fall monthly average 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.’

**Independent variables:** The key predictors of interest consist of 10 dichotomous indicators of COVID-19 mitigation strategies aligned as stringently with CDC guidance as possible[ADD FURTHER DESCRIPTION OF CDC GUIDANCE AND HOW WE ALIGNED WITH IT]. Mitigation strategies were considered in place if they had been updated on the district website during the fall of 2021. These 10 strategy indicators include:

* *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*: Students maintain at least 3 feet of physical distance between each other indoors.
* *Screening testing for students*: Encouraged/recommended/offered screening testing of students on a regular basis.
* *Staying home when sick*: Encouraged or recommended 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/recommended/offered use of high-efficiency particulate air (HEPA) filters.
* *HVAC systems*: Encouraged/recommended/offered 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
* *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 (should we list them?)

## Analyses

In total, policy documents from 1,184 of 1,286 (92%) of the districts were collected, with 28 of the 51 health departments (55%) reporting on 641 schools (40% of total sample). Schools without at least one month of 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 of mitigation strategy, and Pearson’s correlation coefficient between changes in 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; secondly, estimation of a full model including all strategies for relative comparison; and third a model to compare schools having multiple strategies in place, characterized by a cumulative index. The cumulative index is calculated as the sum of strategies identified from the first set of models as having at least a marginal association (p-value < .10) with change in case rates.

# 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 all analyses, resulting in an initial sample of 342 schools. Table 1 provides summary statistics with this sample. Three hundred forty-two schools had case data available for fall and spring, with an overall average of 1.16 (SD = 1.87) more cases per 100 students per month during the spring of 2022 than fall 2021. Surprisingly, none of the school-level covariates nor county-level predictors were significantly associated with changes in case rates, suggested by lack of correlation (last column). For region, state, and locale, ICCs indicated significant clustering by region (ICC = .08) and state (.22), though not by district (.00). This indicates that accounting for clustering of schools by region and state was necessary for modeling. 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 one displays minimum, maximum, mean, and standard deviation of case rates.

Table 2 reviews summary statistics and t-test results of the 10 prevention strategies with changes in case rates as the outcome variable. *No policy* reflects the change in case rate among schools not having the policy in place, whereas *Has policy* indicates the change in case rate among schools having the policy. *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 the HVAC systems district policy experienced an increase in case rates that was .48 per 100 students less than schools not having the policy. Likewise, schools with physical distancing policy in place had an increase that was .38 cases per 100 students less than comparison schools.

Table three shows results from the first set of multilevel models 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, including physical distancing (coefficient = -.38; p-value = .07), staying home when sick (-.33; .08), and HVAC systems (-.38; .06). These three strategies were selected for calculation of the cumulative index reviewed below.

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 five shows results from the multilevel model including the cumulative index as the predictor of interest. Given that three strategies were selected for inclusion in the sum score, the index was treated as ranked ordinal, with a minimum of zero (baseline) and maximum of three. 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), and percent student body two or more races retained statistical significance as well (.24; .03 - .46). Finally, percent student body on free and reduced lunch was associated with a marginally significant decrease (-.28; -.58 - .05).

# Discussion

This study provides evidence that public district guidance of COVID-19 mitigation strategies can help to reduce the spread of COVID-19 in schools. Specifically, we find that districts’ communication of three key strategies to schools, including HVAC systems, physical distancing, and staying home when sick, marginally attenuates COVID-19 spread. However, there is stronger evidence suggesting the effect of the combination of all three strategies, indicated by a statistically significant association between changes in case rates and the cumulative index. Schools residing in districts that publicly updated guidance to require physical distancing, staying home when sick, and HVAC systems during fall 2021 had a significantly reduced increase in case rates than schools with none of the strategies, whereas there was not a significant association with having only one or two of updated policies posted. As such, these results offer a number of key takeaways to inform ongoing efforts to equitably construct safer school environments in the context of current and future public health crises.

First, as suggested by a growing body of literature, the spread of airborne disease among children and adolescents attending public schools can be mitigated, notable 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 communicate that schools should utilize multiple, if not all, mitigation strategies. Furthermore, the heterogeneity of school COVID-19 spread between regions and states highlights the differences in students’ experiences through a broad environmental backdrop of the pandemic.

Secondly, district-published strategy recommendations and requirements served as a proxy for implementation on the ground level, and even though we do not understand schools’ implementation fidelity nor additional strategies that schools may have employed on their own, these results demonstrate the power of districts to successfully guide schools through public health crises utilizing transparent communication approaches. As such, there is an opportunity for federal and state public health agencies to 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 51 health departments as well as low percentage of schools actually having data to be reported indicates a gap in relations with federal agencies. 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 also a number of limitations to consider in the context of the current study, and should be addressed in future research. First, sample size significantly limited our ability to detect smaller effects resulting from strategy usage. The low sample size is partially due to the amount of resources needed to conduct a nationally-representative study, but it is also a result of hesitation of health departments to collaborate with the team, 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 into responding with data. In order for conducting more robust research and evaluation with respect to public health responses and interventions, 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.

Secondly, 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 a cumulative index from those meeting a particular threshold of association with the outcome (p-value < .10). As a means of checking the sensitivity of the results to the cumulative index we also developed cumulative indices using p-values of .2, .3, and .5 as relative cutoffs. These results were conflicting, as …..An alternative methodology for future research may be to explore non-parametric methods, some of which being more conducive to the presence 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 modeling 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 district websites for policies and scoring them for recommendation of strategies 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 during the fall of 2021, and assessing this data for policies were being updated for school guidance. While utilizing machine learning methods to score publicly-posted policy data illustrates the benefits to adopting new technologies and methods, better incorporation of time (e.g., more months, using weekly data) 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.