American Journal of Infection Control 49 (2021) 503−505

Contents lists available at ScienceDirect

American Journal of Infection Control

journal homepage: www.ajicjournal.org

Brief Report

The impact of statewide school closures on COVID-19 infection rates

Elena D. Staguhn BS, Elias Weston-Farber BS, Renan C. Castillo PhD *

Department of Health Policy and Management, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD

Key Words:
Coronavirus
Nonpharmaceutical interventions
Epidemiology

Daily COVID-19 infection rates were examined before and after statewide school closure orders. Regression techniques were used to model changes in the number of confirmed cases and data was combined across states using meta analyses. School closures were found to have a significant impact on infection rates, and thus, may be considered a viable intervention to lower COVID-19 infection rates.

BACKGROUND

COVID-19 has grown into a global pandemic. In the absence of known medical treatments or vaccinations, the United States turned to social distancing. As an initial response to the virus, state governors began closing schools and turning to virtual learning throughout the month of March 2020. By early April 2020, 42 states and the District of Columbia also had a statewide stay-at-home order in place.[1] The shutdown of in-person education and non-essential businesses have led to societal and economic costs.[2]

Nonpharmaceutical interventions were discussed in a previous publication examining the impact of statewide stay-at-home orders on COVID-19 infection rates.[1] We refine the analysis by posing an additional question about the impact of school closures on COVID-19 infection rates. In this report, we examine (1) whether two slopes (pre and post school closure) better fit the data and (2) whether there is a significant reduction in COVID-19 infections due to the school closures.

METHODS

Data Sources

Confirmed daily COVID-19 cases were obtained from the Johns Hopkins Center for Health Security Application and downloaded via GitHub. Stay-at-home order and school closure dates in response to the COVID-19 pandemic were gathered from state government webpages. Statewide stay-at-home orders were announced between March 19 and April 7, 2020,[1] and statewide school closures were announced between March 13 and March 27, 2020. Twenty states and the District of Columbia were excluded from this analysis because they met one of the following criteria: (1) states without statewide stay-at-home orders, (2) states with stay-at-home order dates preceding school closure dates, (3) states with less than 3 days between the date of 10 cases and the school closure date, and (4) states with less than 3 days between the school closure date and the stay-at-home order.

Analysis

Dates of statewide closures were matched with confirmed COVID-19 case counts. The data was separated into counts before and after the school closure date. Raw and logged linear regression techniques were used to calculate the rates of infection for each state. Logged results showed a better fit to the data and were presented throughout.

A spline regression was used to determine the R^2 fit of two slopes: (1) the infection rate from the date of 10 confirmed COVID-19 cases to the date of the school closure and (2) the infection rate from the date of the school closure to the date of the statewide stay-at-home order. This spline regression was compared to a linear regression presenting the R^2 fit of one slope: the infection rate from the date of 10 confirmed COVID-19 cases to the date of the statewide stay-at-home order. Analyses were conducted in RStudio. The METAN command suite in Stata was used to run meta analyses and combine data across states.

RESULTS

A paired t test was run to compare the R^2 fit of the linear regression and the spline regression. The linear regression estimates 1 slope between the date of 10 COVID-19 cases and the date of the stay-at-home order. The spline regression estimates 2 slopes: 1 slope from the date of 10 COVID-19 cases to the date of the school closure and another slope from the date of the school closure to the date of the

* Address correspondence to Renan C. Castillo, PhD, Johns Hopkins Bloomberg School of Public Health, Department of Health Policy and Management, 415 North Washington Street, Baltimore, MD 21231.

E-mail address: rcastil1@jhu.edu (R.C. Castillo).

Conflicts of interest: None to report.

https://doi.org/10.1016/j.ajic.2021.01.002
0196-6553/

Table 1
Infection rates before and after school closures went into effect*,†

State	Order date	Number of days before order	Infection rate and 95% confidence interval (before order)	R^2 (before order)	Number of days after order	Infection rate and 95% confidence interval (after order)	R^2 (after order)
Alabama	3/18/2020	4	0.213 (−0.011, 0.437)	0.893	16	0.086 (0.077, 0.095)	0.967
Arizona	3/16/2020	3	0.088 (−0.558, 0.734)	0.75	14	0.138 (0.123, 0.152)	0.974
Connecticut	3/17/2020	5	0.183 (0.109, 0.257)	0.954	5	0.115 (0.046, 0.185)	0.903
Florida	3/17/2020	10	0.143 (0.128, 0.158)	0.984	16	0.096 (0.091, 0.101)	0.992
Georgia	3/18/2020	10	0.143 (0.129, 0.156)	0.987	15	0.086 (0.081, 0.092)	0.989
Hawaii	3/19/2020	3	0.199 (0.031, 0.367)	0.996	5	0.099 (0.038, 0.16)	0.899
Illinois	3/17/2020	8	0.138 (0.106, 0.17)	0.95	3	0.166 (−0.013, 0.346)	0.993
Indiana	3/19/2020	9	0.088 (0.071, 0.104)	0.957	4	0.169 (0.121, 0.218)	0.991
Kentucky	3/16/2020	5	0.075 (0.043, 0.108)	0.949	9	0.113 (0.098, 0.129)	0.977
Louisiana	3/16/2020	5	0.204 (0.093, 0.315)	0.92	6	0.134 (0.108, 0.161)	0.98
Maryland	3/16/2020	5	0.121 (0.045, 0.198)	0.895	13	0.106 (0.102, 0.11)	0.996
Massachusetts	3/17/2020	10	0.113 (0.08, 0.147)	0.882	6	0.098 (0.09, 0.105)	0.997
Michigan	3/16/2020	4	0.16 (0.087, 0.233)	0.978	7	0.201 (0.172, 0.23)	0.984
Minnesota	3/18/2020	6	0.156 (0.096, 0.215)	0.929	8	0.085 (0.073, 0.097)	0.981
Missouri	3/19/2020	3	0.239 (−0.22, 0.697)	0.978	17	0.098 (0.086, 0.111)	0.95
Nevada	3/16/2020	5	0.135 (0.028, 0.242)	0.844	15	0.094 (0.086, 0.102)	0.98
New Mexico	3/16/2020	4	0.097 (−0.021, 0.214)	0.863	7	0.089 (0.076, 0.102)	0.984
New York	3/18/2020	15	0.153 (0.138, 0.167)	0.971	3	0.157 (0.07, 0.243)	0.998
North Carolina	3/16/2020	5	0.11 (0.082, 0.139)	0.98	13	0.103 (0.094, 0.113)	0.98
Ohio	3/17/2020	5	0.178 (0.107, 0.248)	0.956	5	0.152 (0.141, 0.164)	0.998
Oregon	3/16/2020	9	0.067 (0.052, 0.083)	0.939	6	0.081 (0.071, 0.091)	0.992
Pennsylvania	3/16/2020	7	0.133 (0.099, 0.167)	0.952	15	0.12 (0.114, 0.126)	0.993
Rhode Island	3/16/2020	4	0.073 (−0.082, 0.228)	0.671	11	0.09 (0.081, 0.099)	0.984
South Carolina	3/16/2020	6	0.082 (−0.034, 0.199)	0.822	21	0.083 (0.075, 0.09)	0.969
Tennessee	3/20/2020	9	0.134 (0.116, 0.153)	0.977	12	0.083 (0.073, 0.093)	0.971
Texas	3/20/2020	13	0.132 (0.121, 0.143)	0.984	12	0.085 (0.079, 0.09)	0.991
Vermont	3/18/2020	3	0.017 (−0.11, 0.145)	0.75	6	0.127 (0.098, 0.156)	0.973
Virginia	3/16/2020	5	0.136 (0.024, 0.248)	0.832	13	0.095 (0.092, 0.098)	0.998
Washington	3/17/2020	17	0.118 (0.107, 0.129)	0.973	5	0.07 (0.043, 0.096)	0.959
Wisconsin	3/18/2020	6	0.153 (0.113, 0.194)	0.965	6	0.097 (0.071, 0.123)	0.964

*The COVID-19 infection rates above are logged slopes.
†Results shown above were last updated on August 19, 2020.

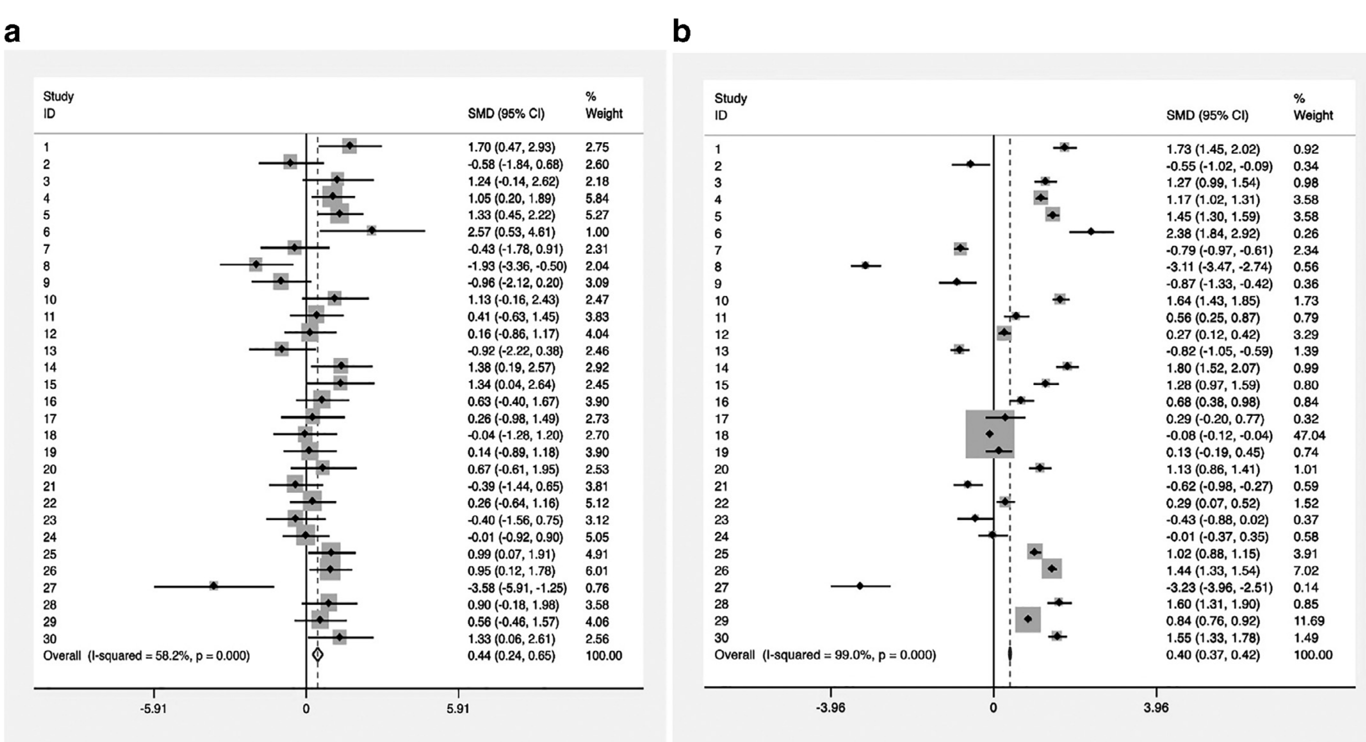

Fig 1. (a) Meta-analysis weighed by the number of days. Ninety-five percent confidence intervals (CI) and standardized mean difference (SMD) are shown. (b) Meta-analysis weighed by the final number of cases. Ninety-five percent confidence intervals (CI) and standardized mean difference (SMD) are shown.

stay-at-home order. There was a significant difference between the 2 regression types, with the spline regression having higher R^2 fits overall ($P< .001$). Thus, we concluded 2 slopes better fit the data.

Next, the difference between the 2 slopes was determined. The average rate of increase in logged COVID-19 infection cases preschool closures was 0.131 (95% C.I.: 0.120, 0.141) per day and from post-school closures through stay-at-home orders was 0.104 (95% C.I.: 0.097, 0.111) per day. Infection rates and 95% confidence intervals pre and post school closures are shown in Table 1. The number of days accounted for per state are also displayed.

Data was combined across states in the meta analyses presented in Figure 1. Root Mean Square Error was used to determine the standard deviation of the infection rates throughout the analyses. Looking at infection rates pre and post school closure through the stay-at-home order and weighing by the number of days yielded a pooled standardized mean difference of 0.44 (95% C.I.:0.24, 0.65; $P< .0001$). Weighing by the number of cases yielded a pooled standardized mean difference of 0.40 (95% C.I.: 0.37, 0.42; $P< .0001$).

DISCUSSION

Although stay-at-home orders play a significant role in preventing the spread of infection,[1] other mandates such as school closures should not be discounted. The results shown here indicate that school closures have a significant impact on COVID-19 infection rates. Thus, virtual or remote learning for students may be an impactful intervention. A recent study supports the conclusion that school closures are an effective preventative measure. Specifically, reductions in community transmission and hospitalization rates resulted from school closures in Hong Kong.[3]

There are several limitations in this study. Nonpharmaceutical interventions co-occurring with school closures may be influencing effects seen in the data. If school closures were implemented at the peak of the epidemic, the threat of regression to the mean must be considered. Finally, the availability of COVID-19 testing may have an unmeasured impact on case counts. Nevertheless, multiple statistical analyses presented in this study show consistent results. Updated daily infection rates and statewide orders can be found at www.hpmcovidpolicy.org.

CONCLUSIONS

Based on our results, school closures are a favorable preventative measure. The data may inform education systems across the nation debating reopening during a pandemic.

References

1. Castillo RC, Staguhn ED, Weston-Farber E. The effect of state-level stay-at-home orders on COVID-19 infection rates. *Am J Infect Control*. 2020;48:958–960.
2. Ozili PK, Arun T. Spillover of COVID-19: impact on the global economy. *SSRN Electr J*. 2020.
3. Cowling BJ, Ali ST, Ng TWY, et al. Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study. *Lancet Public Health*. 2020;5:e279–e288.