cemmap

centre for microdata methods and practice

The association of opening K-12 schools and colleges with the spread of COVID-19 in the United States: country-level panel data analysis

Victor Chernozhukov
Hiroyuki Kasahara
Paul Shrimpf

The Institute for Fiscal Studies
Department of Economics, UCL

cemmap working paper CWP05/21

Economic and Social Research Council

THE ASSOCIATION OF OPENING K-12 SCHOOLS AND COLLEGES WITH THE SPREAD OF COVID-19 IN THE UNITED STATES: COUNTY-LEVEL PANEL DATA ANALYSIS

VICTOR CHERNOZHUKOV, HIROYUKI KASAHARA, AND PAUL SCHRIMPF

Abstract. This paper empirically examines how the opening of K-12 schools and colleges is associated with the spread of COVID-19 using county-level panel data in the United States. Using data on foot traffic and K-12 school opening plans, we analyze how an increase in visits to schools and opening schools with different teaching methods (in-person, hybrid, and remote) is related to the 2-weeks forward growth rate of confirmed COVID-19 cases. Our debiased panel data regression analysis with a set of county dummies, interactions of state and week dummies, and other controls shows that an increase in visits to both K-12 schools and colleges is associated with a subsequent increase in case growth rates. The estimates indicate that fully opening K-12 schools with in-person learning is associated with a 5 (SE = 2) percentage points increase in the growth rate of cases. We also find that the positive association of K-12 school visits or in-person school openings with case growth is stronger for counties that do not require staff to wear masks at schools. These results have a causal interpretation in a structural model with unobserved county and time confounders. Sensitivity analysis shows that the baseline results are robust to timing assumptions and alternative specifications.

1. Introduction

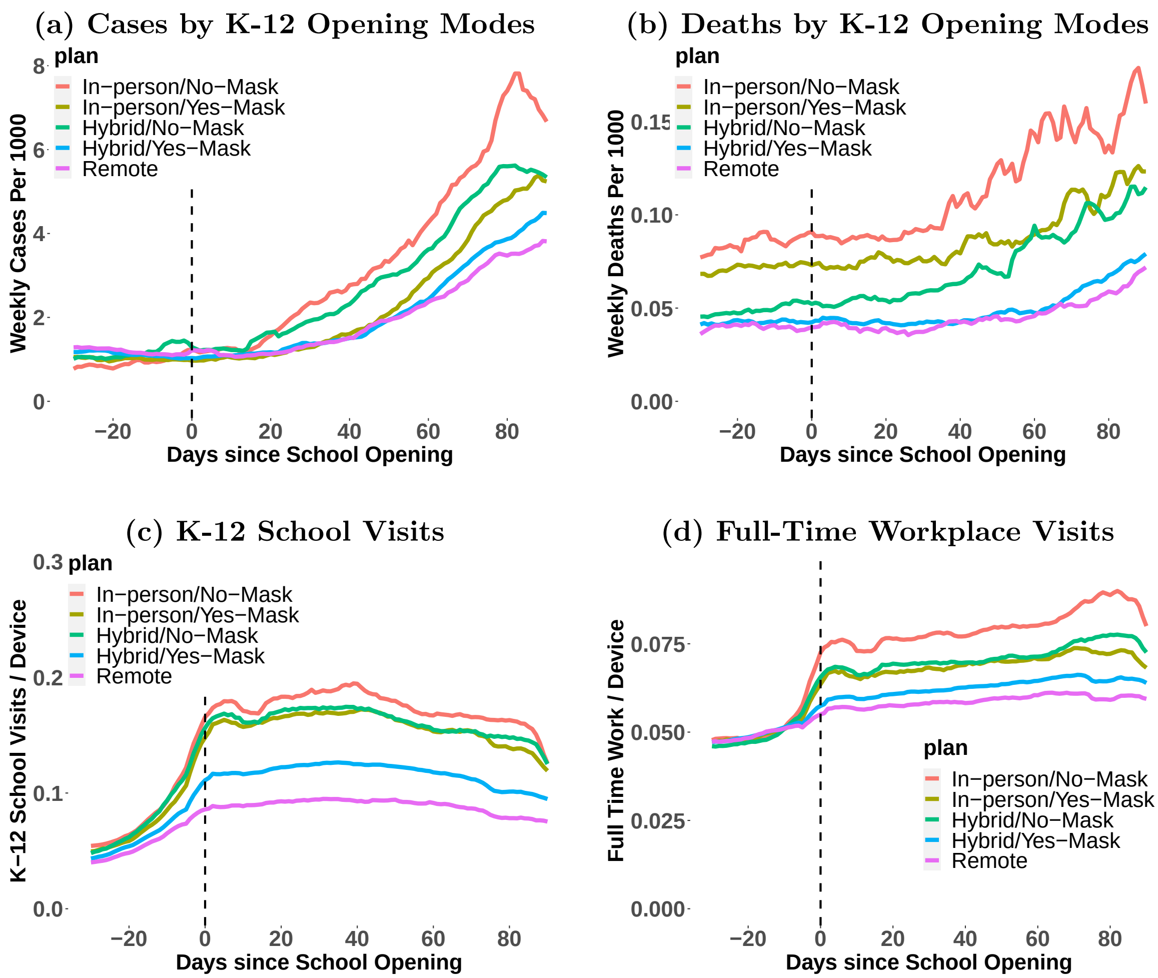
Does opening K-12 schools and colleges lead to the spread of COVID-19? Do mitigation strategies such as mask-wearing requirements help reduce the transmission of SARS-CoV-2 at school? These are important policy relevant questions. If in-person school openings substantially increase COVID-19 cases, then local governments could promote enforcing mitigation measures at schools (universal and proper masking, social distancing, and hand-washing) to lower the risk of COVID-19 spread. Furthermore, the government could prioritize vaccines for education workers in case of in-person school openings. This paper uses county-level panel data on K-12 school opening plans and mitigation strategies together with foot traffic data to investigate how an increase in the visits to K-12 schools and colleges/universities is associated with a subsequent increase in the growth rates of COVID-19 cases in the United States.

Date: February 20, 2021.

Key words and phrases. K-12 school openings | in-person, hybrid, and remote | mask-wearing requirements for staff | foot traffic data | debiased estimator.

We are very grateful to Emily Oster for her helpful comments. All mistakes are our own.

FIGURE 1. The evolution of cases, deaths, and visits to K-12 schools and restaurants before and after the opening of K-12 schools



Notes: (a)-(b) plot the evolution of weekly cases or deaths per 1000 persons averaged across counties within each group of counties classified by K-12 school teaching methods and mitigation strategy of mask requirements against the days since K-12 school opening. We classify counties that implement in-person teaching as their dominant teaching method into "In-person/Yes-Mask" and "In-person/No-Mask" based on whether at least one school district requires staff to wear masks or not. Similarly, we classify counties that implement hybrid teaching into "Hybrid/Yes-Mask" and "Hybrid/No-Mask" based on whether mask-wearing is required for staff. We classify counties that implement remote teaching as "Remote." (c) and (d) plot the evolution of per-device visits to K-12 schools and full-time workplaces, respectively, against the days since K-12 school opening using the same classification as (a) and (b).

We begin with simple suggestive evidence. Fig. 1 provides visual evidence for the association of opening K-12 schools with the spread of COVID-19 as well as the role of school mitigation strategies. Fig. 1(a) and (b) plot the evolution of average weekly cases and deaths per 1000 persons, respectively, against days since school opening across different teaching methods as well as mask requirements for staff. In Fig. 1(a), the average number of weekly cases starts increasing after 2 weeks of opening schools in-person or hybrid, especially for counties with no mask mandates for staff. This possibly suggests that mask mandates at school reduce the transmissions of SARS-CoV-2. In Fig. 1(b), the number of deaths starts increasing after 3 to 5 weeks of opening schools, especially for counties that adopt in-person/hybrid teaching methods with no mask mandates. Alternative mitigation strategies of requiring mask-wearing to the student, prohibiting sports activities, and promoting online instruction also appear to help reduce the number of cases after school openings (see SI Appendix, Fig. S1(i)-(p)).

Fig. 1(c) shows that opening K-12 schools in-person or hybrid increases the number of per-device visits to K-12 schools more than opening remotely, especially when no mask mandates are in place. Fig. 1(d) and SI Appendix, Fig. S1(e)-(f) show that visits to full-time and part-time workplaces increase after school openings with in-person teaching, suggesting that the opening of schools allow parents to return to work. On the other hand, we observe no drastic changes in per-device visits to restaurants, recreational facilities, and churches after school openings (SI Appendix, Fig. S1(b)-(d)).

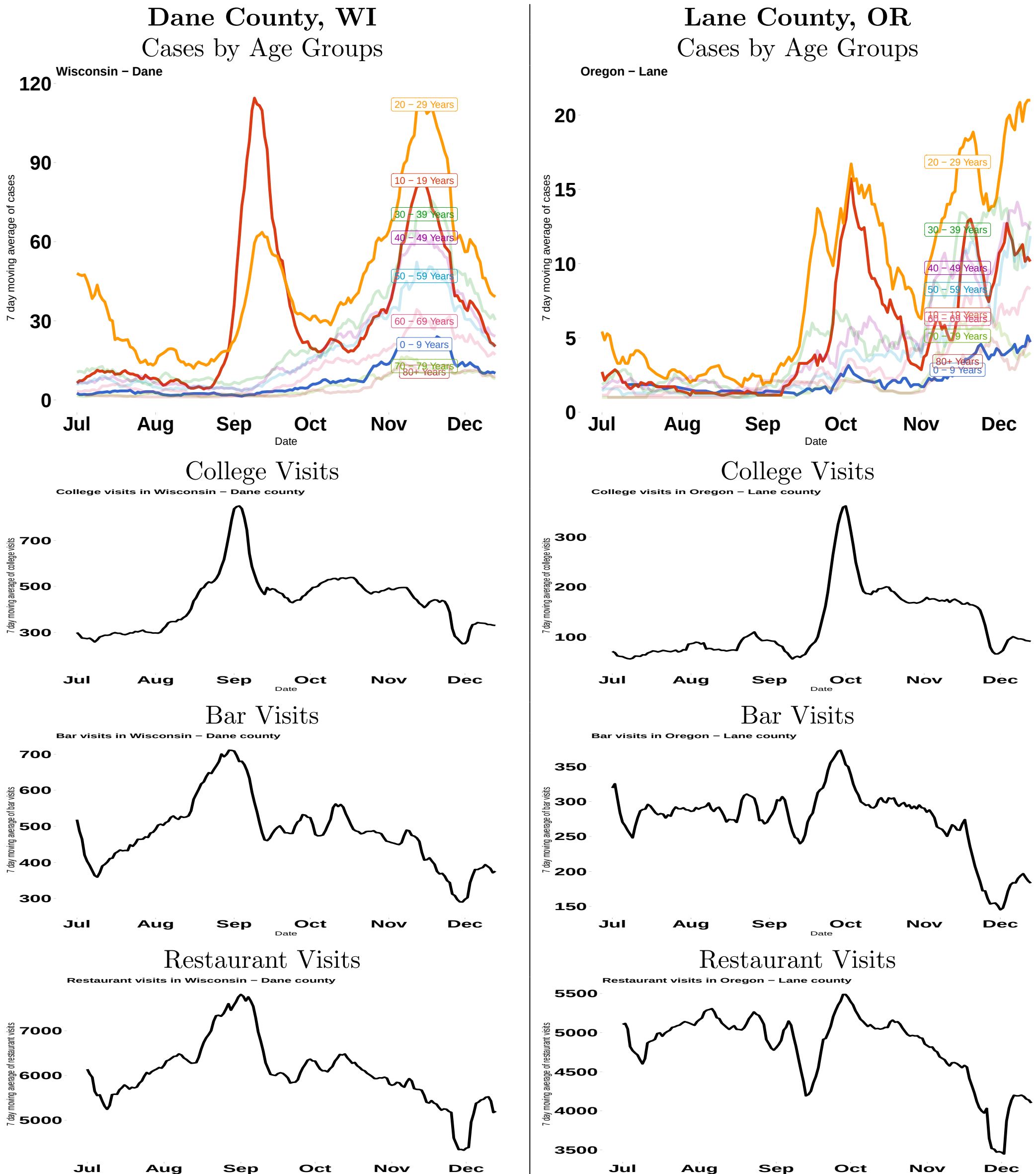
Fig. 2 and SI Appendix, Fig. S2 provide further descriptive evidence that opening colleges and universities with in-person teaching lead to the spread of COVID-19 in counties where the University of Wisconsin(UW)-Madison, the University of Oregon, the University of Arizona, the Michigan State University, the Pennsylvania State University, the Iowa State University, and the University of Illinois-Champaign are located.

What happened in Dane county, WI, is also illustrative. The left panel of Fig. 2 presents the evolution of the number of cases by age groups, the number of visits to colleges and universities, and the number of visits to bars and restaurants in Dane county, WI. The first panel shows that the number of cases for age groups of 10-19 and 20-29 sharply increased in mid-September while few cases were reported for other age groups. The second to the fourth panels suggest that this sharp increase in cases among the 10-29 age cohort in mid-September is associated with an increase in visits to colleges/universities, bars, and restaurants in late August and early September. The fall semester with in-person classes at the UW-Madison began on September 2, 2020, when many undergraduates started living together in residential halls and likely visited bars and restaurants. This resulted in increases in COVID-19 cases on campus; according to the letter from Dane County Executive Joe Parisi to the UW-Madison Parisi (2020), nearly 1,000 positive cases were confirmed on the UW-Madison campus by September 9, 2020, accounting for at least 74 percent of confirmed cases from September 1 to 8, 2020 in Dane county.

While Fig. 1-2 as well as SI Appendix, Fig. S1-S2 are suggestive, the patterns observed in them may be driven by a variety of confounders. Therefore, we analyze the effect of opening K-12 schools and colleges/universities by panel data regression analysis with fixed effects to capture unobserved confounding.

We conduct the analysis using county-level data in the United States. As an outcome variable, we use the weekly growth rate of confirmed cases approximated by the log-difference in reported weekly cases over two weeks, where the log of weekly cases is set to be -1 when we observe zero weekly cases. The main explanatory variables of interest are 2-weeks lagged

FIGURE 2. The number of cases by age groups and the number of visits to colleges/universities and bars in Dane county, WI, and Lane county, OR



Notes: The first, the second, and the third figures in the left panel show the evolution of the number of cases by age groups, the number of visits to colleges/universities, and bars, respectively, in Dane County, WI. The right panel shows the corresponding figures for Lane County, OR.

per-device visits to K-12 schools and colleges/universities from SafeGraph foot traffic data (SI Appendix, Fig. S3. (3)(6)).

We also consider the variable for school openings with different teaching methods (in-person, hybrid, and remote) from MCH Strategic Data (SI Appendix, Fig. S3(11)). Foot traffic data has the advantage over school opening data in that it provides more accurate information on the actual visits to schools over time, possibly capturing unrecorded changes in teaching methods and school closures beyond the information provided by MCH Strategic Data. Furthermore, foot traffic data covers all counties while there is missing information for some school districts in MCH Strategic Data, which may possibly cause sample selection issues.

To investigate the role of mitigation strategies at school on the transmission of SARS-CoV-2, we examine how the coefficients of K-12 school visits and K-12 school opening depend on the mask-wearing requirement for staff by adding an interaction term, for example, between K-12 school visits and mask-wearing requirements for staff at schools.[1]

As confounders, we consider a set of county fixed effects as well as interaction terms between state and week fixed effects to control for unobserved time-invariant county-level factors as well as unobserved time-varying state-level factors. County fixed effects control permanent differences across counties in unobserved personal risk-aversion and attitude toward mask-wearing, hand washings, and social distancing. Interaction terms between state dummy variables and week dummy variables capture any change over time in people's behaviors and non-pharmaceutical policy interventions (NPIs) that are common within a state; they also control for changes in weather, temperature, and humidity within a state. We also include county-level NPIs (mask mandates, ban gathering of more than 50 persons, stay-at-home orders) lagged by 2 weeks to control for the effect of people's behavioral changes driven by policies on case growths beyond the effect of state-level policies.[2] Furthermore, the logarithm of past weekly cases with 2, 3, and 4 weeks lag lengths are included to capture people's voluntarily behavioral response to new information of transmission risks. The growth rate of the number of tests recorded at the daily frequency for each state is also added as a control for case growth regression.

Because the fixed effects estimator with a set of county dummies for dynamic panel regression could be severely biased when the time dimension is short (Nickell, 1981), we employ the debiased estimator by implementing bias correction (e.g., Chen, Chernozhukov, and Fernández-Val, 2019). Our empirical analysis uses 7-day moving averages of daily variables to deal with periodic fluctuations within a week. Our data set contains 3144 counties for regression analysis using foot traffic data but some county observations are dropped out of samples due to missing values for school opening teaching methods and staff

[1]MCH Strategic Data provides the school district level data on whether each school district adopts the following mitigation strategies: (i) mask requirements for staff, (ii) mask requirements for students, (iii) prohibiting sports activities, and (iv) online instruction increases, among other measures. We decided to use mask requirements for staff as the main variable for school mitigation strategy because it has a relatively smaller number of missing values. For regression analysis with the mask requirement variable, we drop counties from the sample when more than 50 percent of students in a county attend school districts of which mask requirements for staff is unknown or pending. Similarly, for specification with different teaching methods, we drop counties from the sample when more than 50 percent of students in a county attend school districts of which teaching methods are unknown or pending.

[2]The decision to reopen schools in some states such as California and Oregon depended on trends in local case counts or hospitalizations (Goldhaber-Fiebert, Studdert, and Mello, 2020).

mask requirements in some regression specifications.[3] Our sample period is from April 1, 2020, to December 2, 2020. The analysis was conducted using R software (version 4.0.3).

Results

Table 1 reports the debiased estimates of panel data regression. Clustered standard errors at the state level are reported in the bracket to provide valid inference under possible dependency over time and across counties within each state. The results suggest that an increase in the visits to K-12 schools and colleges/universities as well as opening K-12 schools with in-person learning mode is associated with an increase in the growth rates of cases with 2 weeks lag when schools implement no mask mandate for staff.

In column (1), the estimated coefficient of per-device visits to colleges is 0.14 (SE = 0.07) while that of per-device visits to K-12 schools is 0.47 (SE = 0.07). The change in top 5 percentile values of per-device visits to colleges/universities and K-12 schools between June and September among counties are around 0.1 and 0.15, respectively, in SI Appendix, Fig. S4(d)(e). Taking these values as a benchmark for full openings, fully opening colleges/universities may be associated with ($0.14\times0.1=$) 1.4 percentage points increase in the growth rates of cases while fully opening K-12 schools may have contributed to ($0.47\times0.15=$) 7 percentage points increase in case growth rates. Column (3) indicates that openings of K-12 schools with the in-person mode are associated with 5 (SE = 2) percentage point increases in weekly case growth rates. It also provides evidence that openings of K-12 schools with remote learning mode are associated with a decrease in case growth, perhaps because remote school opening induces more precautionary behavior to reduce transmission risk.

In column (2), the estimated coefficient of the interaction between K-12 school visits and no mask-wearing requirements for staff is 0.24 (SE=0.07), providing some evidence that mask-wearing requirements for staff may have reduced the transmission of SARS-CoV-2 at schools. Similarly, in column (4), the coefficients on the interaction of in-person and hybrid school openings with no mask mandates are positively estimated as 0.04 (SE=0.02) and 0.05 (SE=0.02), respectively. These estimates likely reflect not only the effect of mask-wearing requirements for staff but also that of other mitigation measures. For example, school districts with staff mask-wearing requirements frequently require students to wear masks.

Other studies on COVID-19 spread in schools have also pointed to the importance of mitigation measures. In contact tracing studies of cases in schools, Gillespie et al. (2021) found that 6 out of 7 traceable case clusters were related to clear noncompliance with mitigation protocols, and Zimmerman et al. (2021) found that most secondary transmissions were related to absent face coverings. Hobbs et al. (2020) find that children who tested positive for COVID-19 are considerably less likely to have had reported consistent mask use by students and staff inside their school.

[3]Our regression analysis uses 2788 counties for specification with K-12 school opening with different teaching modes while the sample contains 2204 counties for specification with mask requirements for staff.

Consistent with evidence from U.S. state-level panel data analysis in Chernozhukov, Kasahara, and Schrimpf (2021), the estimated coefficients of county-wide mask mandate policy are negative and significant in columns (1)-(4), suggesting that mandating masks reduces case growth. The estimated coefficients of ban gatherings and stay-at-home orders are also negative. The negatively estimated coefficients of the log of past weekly cases are consistent with a hypothesis that the information on higher transmission risk induces people to take precautionary actions voluntarily to reduce case growth. The table also highlights the importance of controlling for the test growth rates as a confounder.

Evidence on the role of schools in the spread of COVID-19 from other studies is mixed. Papers that focus on contract tracing of cases among students find limited spread from student infections Zimmerman et al. (2021), Brandal et al. (2021), Ismail et al. (2020), Gillespie et al. (2021), Falk et al. (2021), Willeit et al. (2021). There is also some evidence that school openings are associated with increased cases in the surrounding community. Bignami et al. (2021) provides suggestive evidence that school openings are associated with increased cases in Montreal neighborhoods. Auger et al. (2020) use US state-level data to argue that school closures at the start of the pandemic substantially reduced.

Two closely related papers also examine the relationship between schools and county-level COVID-19 outcomes in the US. Goldhaber et al. (2021) examine the relationship between schooling and cases in counties in Washington and Michigan. They find that in-person schooling is only associated with increased cases in areas with high pre-existing COVID-19 cases. Similarly, Harris, Ziedan, and Hassig (2021) analyze US county-level data on COVID-19 hospitalizations and find that in-person schooling is not associated with increased hospitalizations in counties with low pre-existing COVID-19 hospitalization rates. As discussed in SI Appendix, our regression specification is motivated by a SIRD model, and the dependent variable in our analysis is case growth rates instead of new cases or hospitalizations. Consistent with Goldhaber et al. (2021) and Harris, Ziedan, and Hassig (2021), our finding of a constant increase in growth rates implies a greater increase in cases in counties with more pre-existing cases.

We next provide sensitivity analysis with respect to changes to our regression specification and assumption about delays between infection and reporting cases as follows:

(1) Baseline specifications in columns (1) and (2) of Table 1.
(2),(3) Alternative time lags of 10 and 18 days for visits to colleges and K-12 schools as well as NPIs.
(4) Setting the log of weekly cases to 0 when we observe zero weekly cases to compute the log-difference in weekly cases for outcome variable.
(5) Add the log of weekly cases lagged by 5 weeks and per-capital *cumulative* number of cases lagged by 2 weeks as controls.
(6) Add per-device visits to restaurants, bars, recreational places, and churches lagged by 2 and 4 weeks as controls.
(7) Add per-device visits to full-time and part-time workplaces and a proportion of devices staying at home lagged by 2 weeks as controls.
(8) All of (5)-(7).

Table 1. The Association of School/College Openings and NPIs with Case Growth in the United States: Debiased Estimator

	Dependent variable: Case Growth Rates			
	(1)	(2)	(3)	(4)
College Visits, 14d lag	0.139*	0.070	0.132**	0.010
	(0.071)	(0.073)	(0.064)	(0.076)
K-12 Visits, 14d lag	0.467***	0.386***		
	(0.070)	(0.070)		
K-12 Visits × No-Mask		0.297***		
		(0.070)		
K-12 In-person, 14d lag			0.047***	0.023
			(0.017)	(0.021)
K-12 Hybrid, 14d lag			−0.008	−0.037***
			(0.014)	(0.013)
K-12 Remote, 14d lag			−0.082***	−0.102***
			(0.016)	(0.015)
K-12 In-person × No-Mask				0.041**
				(0.019)
K-12 Hybrid × No-Mask				0.049***
				(0.017)
Mandatory mask, 14d lag	−0.113***	−0.123***	−0.128***	−0.128***
	(0.018)	(0.017)	(0.020)	(0.019)
Ban gatherings, 14d lag	−0.124***	−0.136***	−0.135***	−0.137***
	(0.033)	(0.044)	(0.033)	(0.042)
Stay at home, 14d lag	−0.264***	−0.260***	−0.261***	−0.268***
	(0.031)	(0.039)	(0.034)	(0.040)
log(Cases), 14d lag	−0.101***	−0.101***	−0.098***	−0.099***
	(0.009)	(0.010)	(0.010)	(0.010)
log(Cases), 21d lag	−0.061***	−0.060***	−0.060***	−0.059***
	(0.005)	(0.005)	(0.005)	(0.005)
log(Cases), 28d lag	−0.030***	−0.033***	−0.031***	−0.034***
	(0.003)	(0.003)	(0.004)	(0.004)
Test Growth Rates	0.009**	0.008*	0.009**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
County Dummies	Yes	Yes	Yes	Yes
State× Week Dummies	Yes	Yes	Yes	Yes
Observations	690,297	545,131	612,963	528,941
R^2	0.092	0.093	0.092	0.094

Notes: Dependent variable is the log difference in weekly positive cases across 2 weeks. Regressors are 7-days moving averages of corresponding daily variables and lagged by 2 weeks to reflect the time between infection and case reporting except that we don't take any lag for the log difference in test growth rates. All regression specifications include county fixed effects and state-week fixed effects to control for any unobserved county-level factors and time-varying state-level factors such as various state-level policies. The debiased fixed effects estimator is applied. The results from the estimator without bias correction is presented in SI Appendix, Table S1. Asymptotic clustered standard errors at the state level are reported in bracket. *p<0.1; **p<0.05; ***p<0.01

Because the actual time lag between infection and reporting cases may be shorter or longer than 14 days, we consider the alternative time lags in (2) and (3). Specification (4) checks the sensitivity of handling zero weekly cases to construct the outcome variable of the log difference in weekly cases.

A major concern for interpreting our estimate in Table 1 as the causal effect is that a choice of opening timing, teaching methods, and mask requirements may be endogenous. Our baseline specification mitigates this concern by controlling for county-fixed effects, state-week fixed effects and the log of past cases but a choice of school openings may be still correlated with time-varying unobserved factors at the county-level. Therefore, we estimate a specification with additional time-varying county-level controls in (5)-(8).

Fig. 3(a) takes column (1) of Table 1 as a baseline specification and plots the estimated coefficients for visits to colleges and K12 schools with the 90 percent confidence intervals across different specifications using the debiased estimator; the estimates using the standard estimator *without* bias correction are qualitatively *similar* and reported in SI Appendix, Fig. S3. The estimated coefficients of K-12 school visits and college visits are all positive across different specifications, suggesting that an increase in visits to K-12 schools and colleges is robustly associated with an increase in case growth. On the other hand, the estimated coefficients often become smaller when we add more controls. In particular, relative to the baseline, adding full-time/part-time workplace visits and staying home devices leads to somewhat smaller estimated coefficients for both K-12 school and college visits, suggesting that opening schools and colleges is associated with people returning to work and/or going outside more frequently.

In Fig. 3(b), the estimated interaction term of K-12 school visits and no mask-wearing requirements for staff in column (2) of Table 1 are all positive and significant, robustly indicating a possibility that mask-wearing requirement for staff may have helped to reduce the transmission of SARS-CoV-2 at schools when K-12 schools opened with the in-person teaching method.

Association between School Openings and Mobility. As highlighted by a modeling study for the United Kingdom (Panovska-Griffiths et al., 2020), there are at least two reasons why opening K-12 schools in-person may increase the spread of COVID-19. First, opening K-12 schools increases the number of contacts within schools, which may increase the risk of transmission among children, parents, education workers, and communities at large. Second, reopening K-12 schools allow parents to return to work and increase their mobility in general, which may contribute to the transmission of COVID-19 at schools and workplaces.

To give insight on the role of reopening K-12 schools for parents to return to work and to increase their mobility, we conduct panel data regression analysis by taking visits to full-time workplaces and a measure of staying home devices as outcome variables and use a similar set of regressors as in Table 1 but without taking 2 weeks time lags.

Table 2(a) shows how the proportion of devices at full-time workplaces and that of staying home devices are associated with visits to K-12 schools as well as their in-person openings. In columns (1) and (2), the estimated coefficients of per-device K-12 school visits and opening K-12 schools for full-time work outcome variables are positive and especially large for in-person K-12 school opening. Similarly, the estimates in columns (3) and (4) suggest the negative association of per-device K-12 school visits and opening K-12 schools with the proportion of devices that do not leave their home. This is consistent with a hypothesis that opening K-12 school allows parents to return to work and spend more time outside. This result may also reflect education workers returning to work.

Table 3 presents regression analysis similar to that in Table 1 but including the proportion of devices at full-time/part-time workplaces and those at home as additional regressors, which corresponds to specification (7) in Fig. 3. The estimates indicate that the proportion of staying home devices is negatively associated with the subsequent case growth while the proportion of devices at full-time workplaces is positively associated with the case growth. Combined with the estimates in Table 2(a), these results suggest that school openings may have increased the transmission of SARS-CoV-2 by encouraging parents to return to work and to spend more time outside. This mechanism can partially explain the discrepency between our findings and various studies that focus on cases among students. Contract tracing of cases in schools, such as Falk et al. (2021), Zimmerman et al. (2021), Willeit et al. (2021), Brandal et al. (2021), and Ismail et al. (2020), often finds limited direct spread among students. On the other hand, Vlachos, Hertegård, and B. Svaleryd (2021) finds that parents and teachers of students in open schools experience increases in infection rates.

In columns (1)-(2) of Table 3, the estimated coefficients on K-12 school visits remain positive and large in magnitude even after controlling for the mobility measures of returning to work and being outside home which are mediator variables to capture the indirect effect of school openings on case growth through its effect on mobility. The coefficient on K-12 school visits are approximately 75% as large in Table 3 as in Table 1. This suggests that within-school transmission may be the primary channel through which school openings affect the spread of COVID-19.

One likely reason why college openings may increase cases is that students go out for bars (KA et al., 2020; Chang et al., 2021), where properly wearing masks and practicing social distancing are difficult. Table 2(b) presents how visits to restaurants and bars are associated with colleges/universities from panel regressions using per-device visits to restaurants and bars as outcome variables. These results indicate that bar visits are positively associated with college visits, consistent with a hypothesis that the transmission of SARS-CoV-2 may be partly driven by an increase in visits to bars by students.

Death Growth Regression. Many county-day observations report zero weekly deaths in our data set (SI Appendix, Table S4 and Fig. S4(4)). We approximate the weekly death growth rate by the log difference in weekly deaths, where the log of weekly deaths is replaced with -1 when we observe zero weekly deaths. We also consider an alternative measure of death growth rates by replacing the log of weekly deaths by 0 for zero weekly deaths. For death growth regression, we use the sub-sample of larger counties by dropping 10 percent of the smallest counties in terms of their population size for which zero weekly death happens more frequently.

Fig. 4 illustrates the estimated coefficients of visits to colleges and K-12 schools across different specifications for death growth regressions. SI Appendix, Table S3 presents the estimates of death growth regression under baseline specification with a time lag of 21 days.[4] Fig. 4(a) shows that the coefficient of visits to colleges and K-12 schools are positively estimated for (1) baseline, (3) an alternative time lag of 35 days, (4) an alternative measure of death growth, and adding more controls in (5)-(8), providing evidence that an increase in visits to colleges and K-12 schools is positively associated with the subsequent increase in weekly death growth rates. The magnitude of the estimated coefficient of K-12 school visits becomes smaller when the time lag is set to 28 days in (2). Fig. 4(b) shows that the association of K-12 school visits with death growth is stronger when no mask mandate for staff is in place.

Limitations. Our study has the following limitations. First, our study is observational and therefore should be interpreted with great caution. It only has a causal interpretation in a structural model under exogeneity assumptions that might not hold in reality (see the Model and Method in SI Appendix). While we present sensitivity analysis with a variety of controls including county dummies and interactions of state dummies and week dummies, the decisions to open K-12 schools and colleges/universities may be endogenous and correlated with other unobserved time-varying county-level factors that affect the spread of COVID-19. For example, people's attitudes toward social distancing, hand-washing, and mask-wearing may change over time (which we are not able to observe in the data) and their changes may be correlated with school opening decisions beyond the controls we added to our regression specifications.

Our analysis is also limited by the quality and the availability of the data as follows. The reported number of cases is likely to understate true COVID-19 incidence, especially among children and adolescents because they are less likely to be tested than adults given that children exhibit milder or no symptoms.[5] County-level testing data is not used because of a lack of data although state-week fixed effects control for the weekly difference across counties within the same state and we also control daily state-level test growth rates.

Because foot traffic data is constructed from mobile phone location data, the data on K-12 school visits likely reflects the movements of parents and older children who are allowed

[4]The time lag of 21 days is taken as a baseline to take into account the time lag of infection and death reporting but we also report the estimates for the time lag of 28 and 35 days in specifications (2) and (3). These choices of time lags are motivated by the numbers reported in Table 2 of `https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html`. For the age group above 65, the days from exposure to onset range up to 6 days; the interquartile range of days from symptom onset to death is given by 8 and 21 days; the interquartile range of days from death to reporting is 5 and 44 days.

[5]This is consistent with CDC data which shows the lower testing volume and the higher rate of positive test among children and adolescents than adults (Leidman et al., 2021).

to carry mobile phones to schools and excludes those of younger children who do not own mobile phones.[6]

Because COVID-infected children and adolescents are known to be less likely to be hospitalized or die from COVID, the consequence of transmission among children and adolescents driven by school openings crucially depends on whether the transmission of SARS-CoV-2 from infected children and adolescents to the older population can be prevented.[7] Our analysis does not provide any empirical analysis on how school opening is associated with the transmission across different age groups due to data limitations.[8] Vlachos, Hertegård, and B. Svaleryd (2021) show that teachers in open schools experience higher COVID-19 infection rates compared to teachers in closed schools. They also show that this increase in infection rate also occurs in partners of teachers and parents of students in open schools, albeit to a lesser degree.

The impact of school openings on the spread of COVID-19 on case growth may be different across counties and over time because it may depend not only on in-school mitigation measures but also on contact tracing, testing strategies, and the prevalence of community transmissions (Goldhaber-Fiebert, Studdert, and Mello, 2020; Ziauddeen et al., 2020). We do not investigate how the association between school openings and case growths depends on contact tracing and testing strategies at the county-level.

The result on the association between school opening and death growth in Fig. 4 is suggestive but must be viewed with caution because the magnitude of the estimated coefficient of K-12 school visits is sensitive to the assumption on the time lag from infection to death reporting. The time lag between infection and death is stochastic and spreads over time, making it difficult to uncover the relationship between the timing of school openings and subsequent deaths. Furthermore, while we provide sensitivity analysis for how to handle zero weekly deaths to approximate death growth, our construction of the death growth outcome variable remains somewhat arbitrary.

Finally, our result does not necessarily imply that K-12 schools should be closed. Closing schools have negative impacts on children's learning and may cause declining mental healths among children. The decision to open or close K-12 schools requires careful assessments of the cost and the benefit.

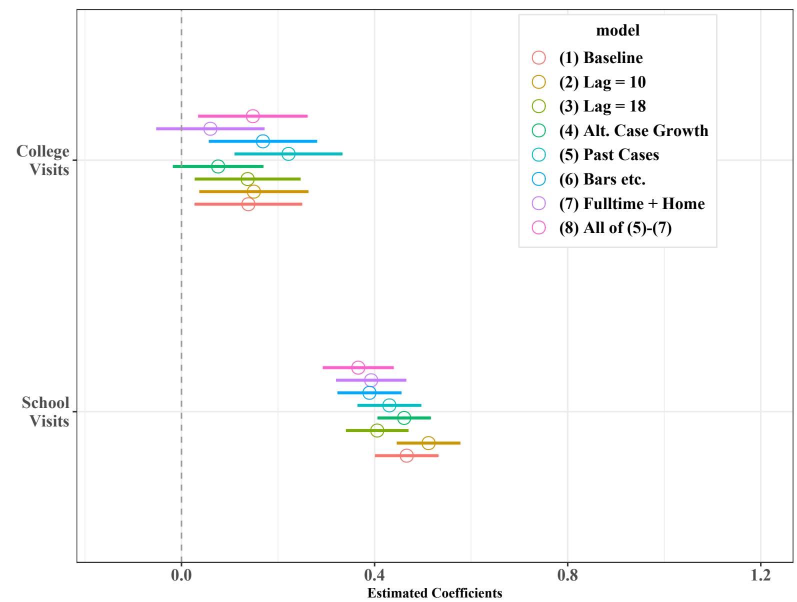
[6]We also focus on limited Points-Of-Interest: K-12 schools, colleges and universities, restaurants, drinking places, other recreational places including gyms, and churches. We check the robustness by including visits to assisted living facilities for the elderly as well as nursing care facilities as additional controls but the results are not sensitive to their inclusion.

[7]In the meta-analysis of 54 studies on the household transmission of SARS-CoV-2 Madewell et al. (2020), estimated household secondary attack rate *to* child contacts was 16.8%. Miyahara et al. (2021) reports that household secondary attack rate *from* children and adolescence to other family members was 23.8% and higher than other age groups in Japan.

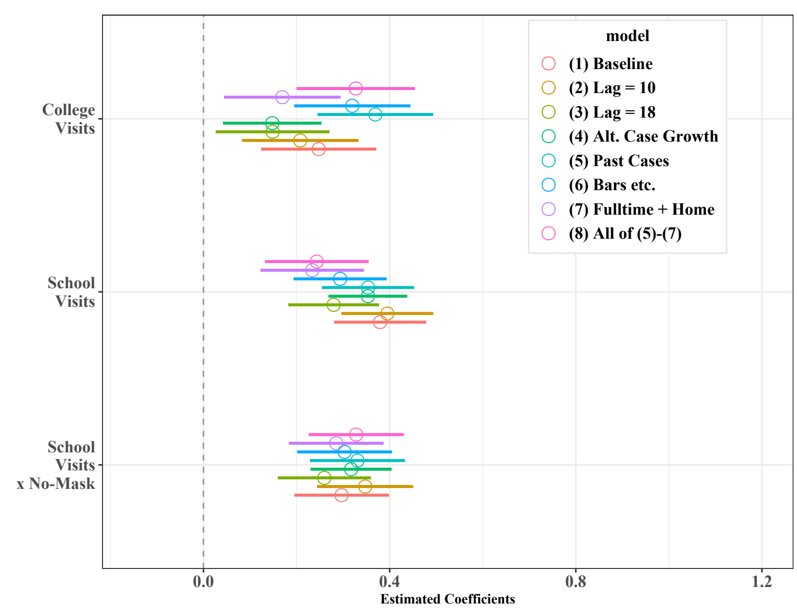
[8]CDC collects the data on the number of reported cases by age groups from each state whenever such data is available. However, for many counties, the reported cases by age groups are missing or there exists a substantial gap between the sum of cases across different age groups reported by CDC and the total number of cases reported in NYT case data (see, for example, the case of Ingham, MI, in SI Appendix, Fig. S2).

FIGURE 3. Sensitivity analysis for the estimated coefficients of K-12 visits and college visits of case growth regressions: Debiased Estimator

(a) Case Growth Estimates



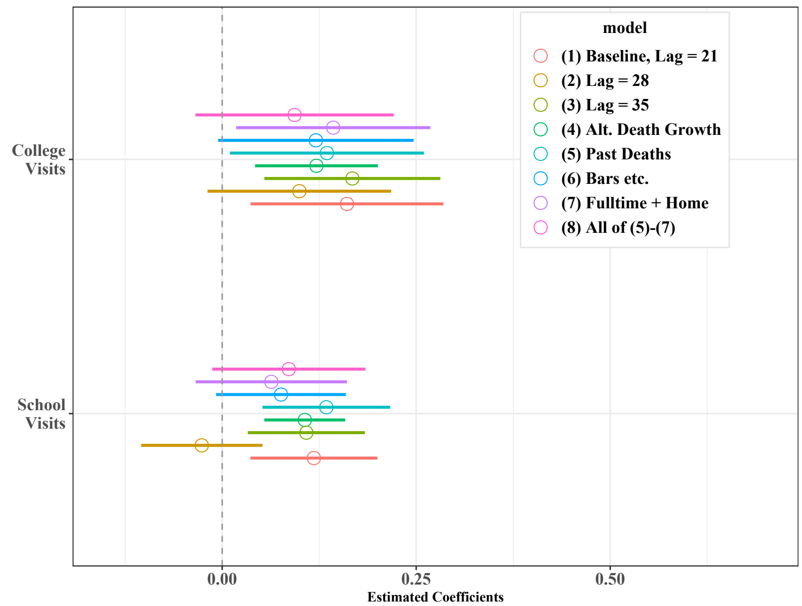
(b) Case Growth Estimates with School Visits × No Mask



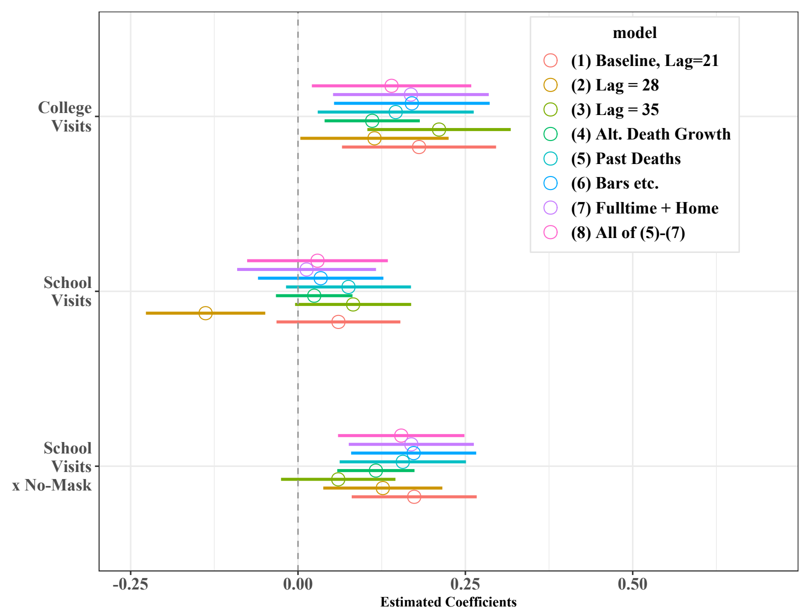
Notes: (a) presents the estimated of college visits and K-12 school visits with the 90 percent confidence intervals across different specifications taking the column (1) of Table 1 as baseline. (b) presents the estimates of college visits , K-12 school visits, and the interaction between K-12 school visits and no mask wearing requirement for staff taking column (2) of Table 1 as baseline. The results are based on the debiased estimator. SI Appendix, Fig. S3 presents the results based on the estimator without bias correction.

FIGURE 4. Sensitivity analysis for the estimated coefficients of K-12 visits and college visits of death growth regressions: Debiased Estimator

(a) Death Growth Estimates



(b) Death Growth Estimates with School Visits × No Mask



Notes: (a) presents the estimated of college visits and K-12 school visits with the 90 percent confidence intervals across different specifications taking the column (1) of SI Appendix, Table S3 as baseline. (b) presents the estimates of college visits , K-12 school visits, and the interaction between K-12 school visits and no mask wearing requirement for staff taking column (2) of SI Appendix, Table S3 as baseline.

Materials and Methods

Data. Cases and the deaths for each county are obtained from the New York Times. SafeGraph provides foot traffic data based on a panel of GPS pings from anonymous mobile devices. Per-device visits to K-12 schools, colleges/universities, restaurants, bars, recreational places, and churches are constructed from the ratio of daily device visits to these point-of-interest locations to the number of devices residing in each county. Full-time and part-time workplace visits are the ratio of the number of devices that spent more than 6 hours and between 3 to 6 hours, respectively, at one location other than one's home location to the total number of device counts. Staying home device variable is the ratio of the number of devices that do not leave home locations to the total number of device counts.

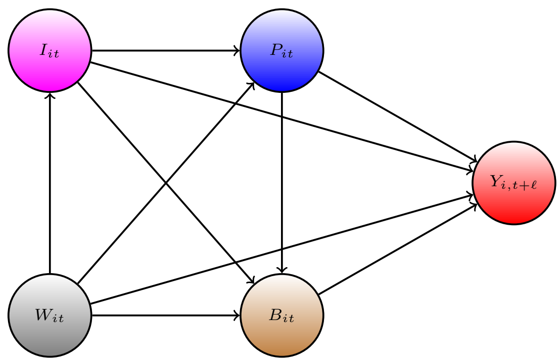
MCH Strategy Data provides information on the date of school openings with different teaching methods (in-person, hybrid, and remote) as well as mitigation strategies at 14703 school districts. We link school district-level MCH data to county-level data from NYT and SafeGraph using the file for School Districts and Associated Counties at US Census Bureau. School district data is aggregated up to county using the enrollment of students at the district level. Specifically, we construct the proportion of students with different teaching methods for each county-day observation using the district level information on school opening dates and teaching methods. We also construct a county-level dummy variable of "No mask requirement for staff" which takes a value of 1 if there exists at least one school district without any mask requirement for staff and 0, otherwise. Our regressors are 7 days moving averages of these variables. A substantial fraction of school districts report "unknown" or "pending" for teaching methods and mask requirements. We drop county observations for which more than 50 percent of students attend school districts that report unknown or pending for teaching methods or mask requirements when these variables are included in regressors.

NPIs data on stay-at-home orders and gathering bans is from Jie Ying Wu Killeen et al. (2020) while the data on mask policies is from Wright et al. (2020). These NPI data contain information up to the end of July; in our regression analysis, we set the value of these policy variables after August to be the same as the value of the last day of observations. Cases by age groups for Fig. 2 is from CDC. SI Appendix, Tables S5-S6 present summary statistics and correlation matrix. Fig. S4. presents the evolution of percentiles of these variables over time.

Methods. Our research design closely follows Chernozhukov, Kasahara, and Schrimpf (2021). Fig. 5 is a causal path diagram for our model that describes how policies, behavior, and information interact together:

- The *forward* health outcome, $Y_{i,t+\ell}$, is determined last after all other variables have been determined;
- The policies, P_{it}, affect health outcome $Y_{i,t+\ell}$ either directly, or indirectly by altering human behavior B_{it}, which may be only partially observed;

Figure 5. The causal path diagram for our model



- Information variables, I_{it}, such as lagged values of outcomes can affect human behavior and policies, as well as outcomes;
- The confounders W_{it}, which vary across counties and time, affect all other variables; these include unobserved but estimable county, time, state, state-week effects.

The index i denotes the county i, and t and $t+\ell$ denotes the time, where ℓ represents the time lag between infection and case confirmation or death. Our health outcomes are the growth rates in Covid-19 cases and deaths and policy variables include school reopening in various modes, mask mandates, ban gathering, and stay-at-home orders, and the information variables include lagged values of outcome (as well as other variables described in the sensitivity analysis).

The causal structure allows for the effect of the policy to be either direct or indirect. For example, school openings not only directly affect case growth through the within-school transmission but also indirectly affect case growth by increasing parents' mobility. The structure also allows for changes in behavior to be brought by the change in policies and information. The information variables, such as the number of past cases, can cause people to spend more time at home, regardless of adopted policies; these changes in behavior, in turn, affect the transmission of SARS-CoV-2.

Our measurement equation will take the form:

$$\Delta \log(\Delta C_{it}) = X'_{i,t-14}\theta + \delta_T \Delta \log(T_{it}) + \epsilon_{it},$$

where i is county, t is day, ΔC_{it} is weekly confirmed cases over 7 days, T_{it} is the number of tests over 7 days, Δ is a 7-day differencing operator, ϵ_{it} is an unobserved error term. $X_{i,t-14}$ collects other behavioral, policy, and confounding variables, where the lag of 14 days captures the time lag between infection and confirmed case (see MIDAS (2020)). In SI Appendix, we relate this specification to the SIRD model.

The main regressors of interest are the visits to K-12 schools and colleges/universities as well as the K-12 school opening variables with different teaching methods together with their interactions with mask requirements for staff. As confounders, $X_{i,t-14}$ includes a set of county dummies and a set of all interaction terms between state dummies and week dummies. We also consider 2, 3, and 4 weeks lagged log values of weekly cases as well as three NPI policy variables. The growth rate of tests, $\Delta \log(T_{it})$, is captured by the observed growth rate of tests at state-level as well as interaction terms between state dummy variables and week dummy variables. The standard errors are computed by clustering at the state-level, where its rationale is that the county-level stochastic shocks may be correlated across counties especially within the state.

Our specification effectively contains the lagged dependent variables in a set of regressors because the log of past weekly cases with different lag lengths can be transformed into the log-differences of past weekly cases. Our model is a dynamic panel regression model in which the fixed effects estimator with a set of county dummies may result in the Nickell bias (Nickell, 1981). To eliminate the bias, we construct an estimator with bias correction as follows.

Given our panel data with sample size (N, T), denote a set of counties by $\mathcal{N} = \{1, 2, ..., N\}$. We randomly and repeatedly partition $\mathcal{N}$ into two sets as $\mathcal{N}_1^j$ and $\mathcal{N}_2^j = \mathcal{N} \setminus \mathcal{N}_1^j$ for $j = 1, 2, ..., J$, where $\mathcal{N}_1^j$ and $\mathcal{N}_2^j$ (approximately) contain the same number of counties. For each of $j = 1, ..., J$, consider two sub-panels (where i stands for county and t stands for the day) defined by $\mathbf{S}_1^j = \mathbf{S}_{11}^j \cup \mathbf{S}_{22}^j$ and $\mathbf{S}_2^j = \mathbf{S}_{12}^j \cup \mathbf{S}_{21}^j$ with $\mathbf{S}_{1k}^j = \{(i,t) : i \in \mathcal{N}_k, t \leq \lceil T/2 \rceil\}$ and $\mathbf{S}_{2k}^j = \{(i,t) : i \in \mathcal{N}_k, t \geq \lfloor T/2 + 1 \rfloor\}$ for $k = 1, 2$, where $\lceil . \rceil$ and $\lfloor . \rfloor$ are the ceiling and floor functions. We form the estimator with bias correction as

$$\widehat{\beta}_{\mathrm{BC}} := \widehat{\beta} - \underbrace{(\widehat{\beta} - \widetilde{\beta})}_{\text{bias estimator}} = 2\widehat{\beta} - \widetilde{\beta} \quad \text{with} \quad \widetilde{\beta} := \frac{1}{J} \sum_{j=1}^{J} \widetilde{\beta}_{\mathbf{S}_1^j \cup \mathbf{S}_2^j},$$

where $\widehat{\beta}$ is the standard estimator with a set of N county dummies while $\widetilde{\beta}_{\mathbf{S}_1^j \cup \mathbf{S}_2^j}$ denotes the estimator using the data set $\mathbf{S}_1^j \cup \mathbf{S}_2^j$ but treats the counties in $\mathbf{S}_1^j$ differently from those in $\mathbf{S}_2^j$ to form the estimator— namely, we include approximately $2N$ county dummies to compute $\widetilde{\beta}_{\mathbf{S}_1^j \cup \mathbf{S}_2^j}$. We choose $J = 2$ in our empirical analysis.[9] We report asymptotic standard errors with state-level clustering, justified by the standard asymptotic theory of bias-corrected estimators.

[9]For some specifications, we also experimented with $J = 5$ and obtained the results similar to those with $J = 2$.

Table 2. The Association of School/College Openings with Mobility in the United States: Debiased Estimator

(a) Full-time Workplace Visits and Staying Home Devices

	Dependent variable			
	Full Time	Full Time	Stay Home	Stay Home
	(1)	(2)	(3)	(4)
College Visits	−0.080***	−0.098***	−0.207***	−0.207***
	(0.004)	(0.006)	(0.024)	(0.026)
K-12 School Visits	0.078***		−0.061**	
	(0.006)		(0.026)	
Open K-12 In-person		0.999***		−2.271***
		(0.125)		(0.382)
Open K-12 Hybrid		0.509***		0.094
		(0.051)		(0.186)
Open K-12 Remote		0.211***		0.159
		(0.048)		(0.307)
Observations	670,909	595,886	670,909	595,886
R^2	0.870	0.853	0.889	0.888
Note:				*p<0.1; **p<0.05; ***p<0.01

(b) Visits to Restaurants and Bars

	Dependent variable			
	Restaurants	Restaurants	Bars	Bars
	(1)	(2)	(3)	(4)
College Visits	0.064	0.034	0.016***	0.012**
	(0.053)	(0.051)	(0.006)	(0.005)
K-12 School Visits	0.006		0.008	
	(0.046)		(0.006)	
Open K-12 In-person		−1.367***		−0.177***
		(0.404)		(0.041)
Open K-12 Hybrid		−1.162***		−0.097***
		(0.272)		(0.038)
Open K-12 Remote		−0.512*		0.031
		(0.295)		(0.056)
Observations	670,909	595,886	670,909	595,886
R^2	0.881	0.883	0.807	0.807

Notes: All regression specifications include county fixed effects, state-week fixed effects, three NPIs variables, and the log of cases without lag, lagged by 1 and 2 weeks. See SI Appendix, Table S1 for the estimated coefficients for NPIs and the log of current and past cases. The debiased estimator is used. Clustered standard errors at the state level are reported in the bracket. SI Appendix, Table S2 reports the estimates for NPIs and past cases. *p<0.1; **p<0.05; ***p<0.01

TABLE 3. The Association of School/College Openings, Full-time/Part-time Work, and Staying Home with Case Growth in the United States: Debiased Estimator

	Dependent variable: ***Case Growth Rates***			
	(1)	(2)	(3)	(4)
College Visits, 14d lag	0.060	0.012	0.114^{*}	0.010
	(0.071)	(0.072)	(0.065)	(0.075)
K-12 Visits, 14d lag	0.393^{***}	0.283^{***}		
	(0.075)	(0.087)		
K-12 Visits × No-Mask		0.287^{***}		
		(0.071)		
K-12 In-person, 14d lag			0.015	−0.007
			(0.016)	(0.020)
K-12 Hybrid, 14d lag			-0.028^{**}	-0.055^{***}
			(0.013)	(0.013)
K-12 Remote, 14d lag			-0.094^{***}	-0.115^{***}
			(0.015)	(0.014)
K-12 In-person × No-Mask				0.034^{*}
				(0.020)
K-12 Hybrid × No-Mask				0.043^{***}
				(0.017)
Full-time Work Device, 14d lag	−0.117	0.186	0.956^{**}	0.967^{**}
	(0.417)	(0.490)	(0.384)	(0.436)
Part-time Work Device, 14d lag	0.262	0.466	0.820^{***}	0.915^{***}
	(0.259)	(0.305)	(0.276)	(0.309)
Staying Home Device, 14d lag	-0.290^{***}	-0.283^{***}	-0.352^{***}	-0.332^{***}
	(0.057)	(0.069)	(0.061)	(0.067)
Observations	690,297	545,131	612,963	528,941
R^2	0.092	0.093	0.092	0.094

Notes: Dependent variable is the log difference in weekly positive cases across 2 weeks. All regression specifications include county fixed effects and state-week fixed effects, three NPIs, and 2, 3, and 4 weeks lagged log of cases. See SI Appendix, Table S3 for the estimated coefficients for NPIs and the log of current and past cases. The debiased fixed effects estimator is applied. Asymptotic clustered standard errors at the state level are reported in the bracket.
*p<0.1; **p<0.05; ***p<0.01

REFERENCES

Auger, Katherine A., Samir S. Shah, Troy Richardson, David Hartley, Matthew Hall, Amanda Warniment, Kristen Timmons, Dianna Bosse, Sarah A. Ferris, Patrick W. Brady, Amanda C. Schondelmeyer, and Joanna E. Thomson. 2020. "Association Between Statewide School Closure and COVID-19 Incidence and Mortality in the US." *JAMA* 324 (9):859–870. URL `https://doi.org/10.1001/jama.2020.14348`.

Bignami, Simona, Yacine Boujija, John Sandberg, and Olivier Drouin. 2021. "Enfants, écoles et COVID-19 : le cas montréalais."

Brandal, Lin T, Trine S Ofitserova, Hinta Meijerink, Rikard Rykkvin, Hilde M Lund, Olav Hungnes, Margrethe Greve-Isdahl, Karoline Bragstad, Karin Nygård, and Winje Brita A. 2021. "Minimal transmission of SARS-CoV-2 from paediatric COVID-19 cases in primary schools, Norway, August to November 2020." *Euro Surveill* URL `https://doi.org/10.2807/1560-7917.ES.2020.26.1.2002011`.

Chang, Serina, Emma Pierson, Pang Wei Koh, Jaline Gerardin, Beth Redbird, David Grusky, and Jure Leskovec. 2021. "Mobility network models of COVID-19 explain inequities and inform reopening." *Nature* 589 (7840):82–87. URL `https://doi.org/10.1038/s41586-020-2923-3`.

Chen, Shuowen, Victor Chernozhukov, and Iván Fernández-Val. 2019. "Mastering panel metrics: causal impact of democracy on growth." In *AEA Papers and Proceedings*, vol. 109. 77–82.

Chen, Shuowen, Victor Chernozhukov, Ivan Fernandez-Val, Hiroyuki Kasahara, and Paul Schrimpf. 2020. "Cross-Over Jackknife Bias Correction for Non-Stationary Nonlinear Panel Data."

Chernozhukov, Victor, Hiroyuki Kasahara, and Paul Schrimpf. 2021. "Causal impact of masks, policies, behavior on early covid-19 pandemic in the U.S." *Journal of Econometrics* 220 (1):23–62.

Falk, A, A Benda, P Falk, S Steffen, Z Wallace, and TB Høeg. 2021. "COVID-19 Cases and Transmission in 17 K–12 Schools — Wood County, Wisconsin, August 31–November 29, 2020." *Morbidity and Mortality Weekly Report* 70:136–140. URL `http://dx.doi.org/10.15585/mmwr.mm7004e3`.

Gillespie, Darria Long, Lauren Ancel Meyers, Michael Lachmann, Stephen C Redd, and Jonathan M Zenilman. 2021. "The Experience of Two Independent Schools with In-Person Learning During the COVID-19 Pandemic." *medRxiv* URL `https://www.medrxiv.org/content/early/2021/01/29/2021.01.26.21250065`.

Goldhaber, Dan, Scott A Imberman, Katharine O Strunk, Bryant Hopkins, Nate Brown, Erica Harbatkin, and Tara Kilbride. 2021. "To What Extent Does In-Person Schooling Contribute to the Spread of COVID-19? Evidence from Michigan and Washington." Working Paper 28455, National Bureau of Economic Research. URL `http://www.nber.org/papers/w28455`.

Goldhaber-Fiebert, Jeremy D., David M. Studdert, and Michelle M. Mello. 2020. "School Reopenings and the Community During the COVID-19 Pandemic." *JAMA Health Forum* 1 (10):e201294–e201294. URL `https://doi.org/10.1001/jamahealthforum.2020.1294`.

Hahn, Jinyong and Whitney Newey. 2004. "Jackknife and Analytical Bias Reduction for Nonlinear Panel Models." *Econometrica* 72 (4):1295–1319. URL `https://EconPapers.repec.org/RePEc:ecm:emetrp:v:72:y:2004:i:4:p:1295-1319`.

Harris, Douglas N., Engy Ziedan, and Susan Hassig. 2021. "The Effects of School Reopenings on COVID-19 Hospitalizations." Tech. rep. URL `https://www.reachcentered.org/publications/the-effects-of-school-reopenings-on-covid-19-hospitalizations`.

Hobbs, Charlotte V., Lora M. Martin, Sara S. Kim, Brian M. Kirmse, Lisa Haynie, Sarah McGraw, Paul Byers, Kathryn G. Taylor, Manish M. Patel, Brendan Flannery, and CDC COVID-19 Response Team. 2020. "Factors Associated with Positive SARS-CoV-2 Test Results in Outpatient Health Facilities and Emergency Departments Among Children and Adolescents Aged ¡18 Years - Mississippi, September-November 2020." *MMWR. Morbidity and Mortality Weekly Report* 69 (50):1925–1929. URL `https://pubmed.ncbi.nlm.nih.gov/33332298`.

Ismail, Sharif A., Vanessa Saliba, Jamie Lopez Bernal, Mary E. Ramsay, and Shamez N. Ladhani. 2020. "SARS-CoV-2 infection and transmission in educational settings: a prospective, cross-sectional analysis of infection clusters and outbreaks in England." *The Lancet Infectious Diseases* URL `https://doi.org/10.1016/S1473-3099(20)30882-3`.

KA, Fisher, Tenforde MW, Feldstein LR, Christopher J. Lindsell, Nathan I. Shapiro, D. Clark Files, Kevin W. Gibbs, Heidi L. Erickson, Matthew E. Prekker, Jay S. Steingrub, Matthew C. Exline, Daniel J. Henning, Jennifer G. Wilson, Samuel M. Brown, Ithan D. Peltan, Todd W. Rice, David N. Hager, Adit A. Ginde, H. Keipp Talbot, Jonathan D. Casey, Carlos G. Grijalva, Brendan Flannery, Manish M. Patel, and Wesley H. Self. 2020. "Community and Close Contact Exposures Associated with COVID-19 Among Symptomatic Adults $\geq$ 18 Years in 11 Outpatient Health Care Facilities — United States, July 2020." *MMWR Morb Mortal Wkly Rep* 69:1258–1264. URL `http://dx.doi.org/10.15585/mmwr.mm6936a5`.

Killeen, Benjamin D., Jie Ying Wu, Kinjal Shah, Anna Zapaishchykova, Philipp Nikutta, Aniruddha Tamhane, Shreya Chakraborty, Jinchi Wei, Tiger Gao, Mareike Thies, and Mathias Unberath. 2020. "A County-Level Dataset for Informing the United States' Response to COVID-19."

Leidman, Eva, Lindsey M. Duca, John D. Omura, Krista Proia, James W. Stephens, and Erin K. Sauber-Schatz. 2021. "COVID-19 Trends Among Persons Aged 0–24 Years — United States, March 1–December 12, 2020." *MMWR Morb Mortal Wkly Rep* 70. URL `http://dx.doi.org/10.15585/mmwr.mm7003e1`.

Madewell, Zachary J., Yang Yang, Jr Longini, Ira M., M. Elizabeth Halloran, and Natalie E. Dean. 2020. "Household Transmission of SARS-CoV-2: A Systematic Review and Meta-analysis." *JAMA Network Open* 3 (12):e2031756–e2031756. URL `https://doi.org/10.1001/jamanetworkopen.2020.31756`.

MIDAS. 2020. "MIDAS 2019 Novel Coronavirus Repository: Parameter Estimates." URL `https://github.com/midas-network/COVID-19/tree/master/parameter_estimates/2019_novel_coronavirus`.

Miyahara, Reiko, Naho Tsuchiya, Ikkoh Yasuda, Yura Ko, Yuki Furuse, Eiichiro Sando, Shohei Nagata, Tadatsugu Imamura, Mayuko Saito, Konosuke Morimoto, Takeaki Imamura, Yugo Shobugawa, Hiroshi Nishiura, Motoi Suzuki, and Hitoshi Oshitani. 2021. "Familial Clusters of Coronavirus Disease in 10 Prefectures, Japan, February-May 2020." *Emerging Infectious Diseases* 27 (3). URL https://wwwnc.cdc.gov/eid/article/27/3/20-3882_article.

Nickell, Stephen. 1981. "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49 (6):1417–26. URL https://EconPapers.repec.org/RePEc:ecm:emetrp:v:49:y:1981:i:6:p:1417-26.

Panovska-Griffiths, Jasmina, Cliff C Kerr, Robyn M Stuart, Dina Mistry, Daniel J Klein, Russell M Viner, and Chris Bonell. 2020. "Determining the optimal strategy for reopening schools, the impact of test and trace interventions, and the risk of occurrence of a second COVID-19 epidemic wave in the UK: a modelling study." *The Lancet Child & Adolescent Health* 4 (11):817–827.

Parisi, Joe. 2020. "the letter from Dane County Executive to the UW-Madison." https://www.channel3000.com/content/uploads/2020/09/Parisi-letter-to-UW-9-9-20.pdf.

Pearl, Judea. 2009. *Causality.* Cambridge university press.

Vlachos, Jonas, Edvin Hertegård, and Helena B. Svaleryd. 2021. "The effects of school closures on SARS-CoV-2 among parents and teachers." *medRxiv* 118 (9). URL https://www.medrxiv.org/content/early/2021/01/29/2021.01.26.21250065.

White House, The. 2020. "Guidelines for Opening Up America Again." URL https://www.whitehouse.gov/openingamerica/.

Willeit, Peter, Robert Krause, Bernd Lamprecht, Andrea Berghold, Buck Hanson, Evelyn Stelzl, Heribert Stoiber, Johannes Zuber, Robert Heinen, Alwin Köhler, David Bernhard, Wegene Borena, Christian Doppler, Dorothee von Laer, Hannes Schmidt, Johannes Pröll, Ivo Steinmetz, and Michael Wagner. 2021. "Prevalence of RT-PCR-detected SARS-CoV-2 infection at schools: First results from the Austrian School-SARS-CoV-2 Study." *medRxiv* URL https://www.medrxiv.org/content/early/2021/01/06/2021.01.05.20248952.

Wright, Austin L., Konstantin Sonin, Jesse Driscoll, and Jarnickae Wilson. 2020. "Poverty and Economic Dislocation Reduce Compliance with COVID-19 Shelter-in-Place Protocols." *SSRN Electronic Journal* .

Ziauddeen, Nida, Kathryn Woods-Townsend, Sonia Saxena, Ruth Gilbert, and Nisreen A Alwan. 2020. "Schools and COVID-19: Reopening Pandora's box?" *Public Health in Practice* 1:100039–100039. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7486860/. Edition: 2020/12/22 Publisher: The Authors. Published by Elsevier Ltd on behalf of The Royal Society for Public Health.

Zimmerman, Kanecia O., Ibukunoluwa C. Akinboyo, M. Alan Brookhart, Angelique E. Boutzoukas, Kathleen McGann, Michael J. Smith, Gabriela Maradiaga Panayotti, Sarah C. Armstrong, Helen Bristow, Donna Parker, Sabrina Zadrozny, David J. Weber, and Daniel K. Benjamin. 2021. "Incidence and Secondary Transmission of SARS-CoV-2 Infections in Schools." *Pediatrics* URL https://pediatrics.aappublications.org/content/early/2021/01/06/peds.2020-048090.

2. Supplementary Information Appendix

The Model and Methods.

The Structural Causal Model. Our approach draws on the framework presented in our previous paper Chernozhukov, Kasahara, and Schrimpf (2021). Here we summarize the approach for completeness, highlighting the main difference (here we do not assume that all relevant social distancing behavioral variables are observed).

We begin with a qualitative description of the model via a causal path diagram shown in Figure 6, which describes how policies, behavior, and information interact together:

- The *forward* health outcome, $Y_{i,t+\ell}$, is determined last, after all other variables have been determined;
- The adopted vector of policies, P_{it}, affect health outcome $Y_{i,t+\ell}$ either directly, or indirectly by altering individual distancing and other precautioanry behavior B_{it}, which may be only partially observed;
- Information variables, I_{it}, such as lagged values of outcomes and other lagged observable variables (see robustness checks) can affect human behavior and policies, as well as outcomes;
- The confounding factors W_{it}, which vary across counties and time, affect all other variables; these include unobserved though estimable county, time, state, state-week effects.

The index i denotes observational unit, the county, and t and $t + \ell$ denotes the time, where ℓ represents the typical time lag between infection and case confirmation or death.

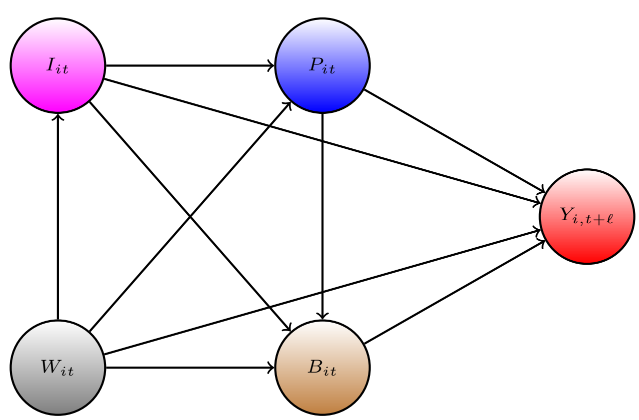


Figure 6. The causal path diagram for our model.

Our main outcomes of interest are the growth rates in Covid-19 cases and deaths and policy variables include school reopening in various modes, mask mandates, ban gathering, and stay-at-home orders, and the information variables include lagged values of outcome (as well as other variables described in the sensitivity checks).

The role of behavioral variables in the model is two-fold. First, the presence of these variables in the model requires us to control for the information variables – even when information variables affect outcomes only through policies or behavior. In this case conditioning on the information blocks the backdoor path (see, Pearl (2009)) creating confounding

$$Y_{i,t+\ell} \longleftarrow B_{it} \longleftarrow I_{it} \longrightarrow P_{it}.$$

Therefore conditioning on the information is important even when there is no direct effect $I_{it} \longrightarrow Y_{i,t+\ell}$. This observation motivates our main dynamic specification below, where information variables include lagged growth rates and new cases or new deaths per capita. Second, while not all behavioral variables may be observable, we can still study as the matter of supporting analysis, the effects of policies on observed behavioral variables (the portion of time in workplace, restaurants, and bars) and of behavioral variables on outcomes, thereby gaining insight as to whether policies have changed private behavior and to what extent this private behavior changed the outcomes (for the analysis, of early pandemic data in this vein, see our previous paper).

The causal structure allows for the effect of the policy to be either direct or indirect. The structure also allows for changes in behavior to be brought by the change in policies and information. These are all realistic properties that we expect from the context of the problem. Policies such as closures and reopenings of schools, closures or reopening of non-essential business, and restaurants, affect the behavior in strong ways. In contrast, policies such as mandating employees to wear masks can potentially affect the Covid-19 transmission directly. The information variables, such as recent growth in the number of cases, can cause people to spend more time at home, regardless of adopted policies; these changes in behavior, in turn, affect the transmission of Covid-19.

The causal ordering induced by this directed acyclical graph is determined by the following timing sequence:

(1) information and confounders get determined at t,
(2) policies are set in place, given information and confounders at t;
(3) behavior is realized, given policies, information, and confounders at t;
(4) outcomes get realized at $t+\ell$ given policies, behavior, information, and confounders.

The model also allows for direct dynamic effects of information variables on the outcome through autoregressive structures that capture persistence in growth patterns. We do not highlight these dynamic effects and only study the short-term effects (longer-run effects get typically amplified; see our previous paper Chernozhukov, Kasahara, and Schrimpf (2021) for more details.)

Our quantitative model for causal structure in Figure 6 is given by the following econometric structural equation model:

$$\begin{aligned} Y_{i,t+\ell}(b,p,\iota) &:= \alpha' b + \pi' p + \mu' \iota + \delta_Y' W_{it} + \varepsilon_{it}^y, \\ B_{it}(p,\iota) &:= \beta' p + \gamma' \iota + \delta_B' W_{it} + \varepsilon_{it}^b, \\ P_{it}(\iota) &:= p(\eta' \iota, W_{it}, \varepsilon_{it}^p), \end{aligned} \tag{SEM}$$

which is a collection of structural potential response functions (potential outcomes), where the stochastic schocks are decomposed into an observable part $\delta' W$ and unobservable part ε. Lower case letters ι, b and p denote the potential values of information, behavior, and policy variables. The restrictions on shocks are described below.

The observed outcomes, policy, and behavior variables are generated by setting $\iota = I_{it}$ and propagating the system from the last equation to the first:

$$\begin{aligned} Y_{i,t+\ell} &:= Y_{i,t+\ell}(B_{it}, P_{it}, I_{it}), \\ B_{it} &:= B_{it}(P_{it}, I_{it}), \\ P_{it} &:= P_{it}(I_{it}). \end{aligned}$$

The orthogonality restrictions on the stochastic components are as follows: The stochastic shocks ε_{it}^y and ε_{it}^p are centered and furthermore,

$$\begin{aligned} \varepsilon_{it}^y &\perp (\varepsilon_{it}^b, P_{it}, W_{it}, I_{it}), \\ \varepsilon_{it}^b &\perp (P_{it}, W_{it}, I_{it}), \\ \varepsilon_{it}^p &\perp\!\!\!\perp (W_{it}, I_{it}), \end{aligned} \tag{O}$$

where we say that $V \perp U$ if $\mathrm{E} VU = 0$. This is a standard way of representing restrictions on errors in structural equation modeling. The last equation states that variation in policies is exogenous conditionally on confounders and information variables.

The system above together with orthogonality restrictions (O) implies the following collection of stochastic equations for realized variables:

$$Y_{i,t+\ell} = \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \delta_Y' W_{it} + \varepsilon_{it}^y, \qquad \varepsilon_{it}^y \perp B_{it}, P_{it}, I_{it}, W_{it} \tag{BPI→Y}$$

$$B_{it} = \beta' P_{it} + \gamma' I_{it} + \delta_B' W_{it} + \varepsilon_{it}^b, \qquad \varepsilon_{it}^b \perp P_{it}, I_{it}, W_{it} \tag{PI→B}$$

As discussed below, the information variable includes case growth. Therefore, the orthogonality restriction $\varepsilon_{it}^y \perp P_{it}$ holds if the government does not have knowledge on future case growth beyond what is predicted by the information set and the confounders; even when the government has some knowledge on ε_{it}^y, the orthogonality restriction may hold if there is a time lag for the government to implement its policies based on ε_{it}^y.

We stress that our main analysis does not require all components of B_{it} to be observable.

Main Implication. The model stated above implies the following projection equation:

$$Y_{i,t+\ell} = a'P_{it} + b'I_{it} + c'W_{it} + \bar{\varepsilon}_{it}, \quad \bar{\varepsilon}_{it} \perp P_{it}, I_{it}, W_{it}, \tag{PI→Y}$$

where

$$a' := (\alpha'\beta' + \pi'), \quad b' := (\alpha'\gamma' + \mu'), \quad c' := (\alpha'\delta'_B + \delta'_Y)$$

This follows immediately from plugging equation (PI → B) to equation (BPI → Y) and verifying that the composite stochastic shock $\bar{\varepsilon}_{it}$ obeys the orthogonality condition stated in (PI→Y).

The main parameter of interest is the structural causal effect of the policy:

$$a' = (\alpha'\beta' + \pi').$$

It comprises direct policy effect π' as well as the indirect effect $\alpha'\beta'$, realized by the policy changing observed and unobserved behavior variables B_{it}. This coefficient a and b can estimated directly using the dynamic panel data methods described in more detail below.

As additional analysis, we can estimate the determinants for the observed behavioral mobility measures– the observed part of B_{it}.

Identification and Parameter Estimation. The orthogonality equations imply that the main equation is the projection equation, and parameters a and b are identified if P_{it} and I_{it} have sufficient variation left after partialling out the effect of controls:

$$\tilde{Y}_{i,t+\ell} \quad = a'\tilde{P}_{it} + c'\tilde{I}_{it} + \bar{\varepsilon}_{it}, \quad \bar{\varepsilon}_{it} \perp \tilde{P}_{it}, \tilde{I}_{it}, \tag{1}$$

where $\tilde{V}_{it} = V_{it} - W'_{it}\mathrm{E}[W_{it}W'_{it}]^{-}\mathrm{E}[W_{it}V_{it}]$ denotes the residual after removing the orthogonal projection of V_{it} on W_{it}. The residualization is a linear operator, implying that (1) follows immediately from the above. The parameters of (1) are identified as projection coefficients in these equations, provided that residualized vectors have non-singular variance matrix:

$$\mathrm{Var}(\tilde{P}'_{it}, \tilde{I}'_{it}) > 0. \tag{2}$$

Our main estimation method is the fixed effects estimator, where the county, state, state-week effects are treated as unobserved components of W_{it} and estimated directly from the panel data, so they are rendered (approximately) observable once the history is sufficiently long. The stochastic shocks $\{\varepsilon_{it}\}_{t=1}^{T}$ are treated as independent across states and can be arbitrarily dependent across time t within a state. In other words, the standard errors will be clustered at the state level. When histories are not long, substantial biases emerge from working with the estimated version $\widehat{W}_{it}$ of W_{it} (known as the Nickel bias (Nickell, 1981)) and they need to be removed using debiasing methods. In our context, debiasing changes the magnitudes of the original biased fixed effect estimator but does not change the qualitative conclusions reached without any debiasing.

Formulating Outcome and Key Confounders via SIR model. Letting C_{it} denote the cumulative number of confirmed cases in county i at time t, our outcome

$$Y_{it} = \Delta \log(\Delta C_{it}) := \log(\Delta C_{it}) - \log(\Delta C_{i,t-7}) \tag{3}$$

approximates the weekly growth rate in new cases from $t-7$ to t.[10] Here Δ denotes the differencing operator over 7 days from t to $t-7$, so that $\Delta C_{it} := C_{it} - C_{i,t-7}$ is the number of new confirmed cases in the past 7 days.

We chose this metric as this is the key metric for policymakers deciding when to relax Covid mitigation policies. The U.S. government's guidelines for state reopening recommend that states display a "downward trajectory of documented cases within a 14-day period" (White House, 2020). A negative value of Y_{it} is an indication of meeting these criteria for reopening. By focusing on weekly cases rather than daily cases, we smooth idiosyncratic daily fluctuations as well as periodic fluctuations associated with the days of the week.

Our measurement equation for estimating equations (BPI→Y) and (PI→Y) will take the form:

$$\Delta \log(\Delta C_{it}) = X'_{i,t-14}\theta + \delta_T \Delta \log(T_{it}) + \epsilon_{it}, \tag{M-C}$$

where i is county, t is day, C_{it} is cumulative confirmed cases, T_{it} is the number of tests over 7 days, Δ is a 7-days differencing operator, ϵ_{it} is an unobserved error term. $X_{i,t-14}$ collects other behavioral, policy, and confounding variables, depending on whether we estimate (BPI→Y) or (PI→Y), where the lag of 14 days captures the time lag between infection and confirmed case (see MIDAS (2020)). Here

$$\Delta \log(T_{it}) := \log(T_{it}) - \log(T_{i,t-7})$$

is the key confounding variable, derived from considering the SIR model below. We describe other confounders in the empirical analysis section.

Our main estimating equation (M-C) is motivated by a variant of SIR model, where we add confirmed cases and infection detection via testing. Let S, $\mathcal{I}$, R, and D denote the number of susceptible, infected, recovered, and dead individuals in a given state. Each of these variables are a function of time. We model them as evolving as

$$\dot{S}(t) = -\frac{S(t)}{N}\beta(t)\mathcal{I}(t) \tag{4}$$

$$\dot{\mathcal{I}}(t) = \frac{S(t)}{N}\beta(t)\mathcal{I}(t) - \gamma\mathcal{I}(t) \tag{5}$$

$$\dot{R}(t) = (1-\kappa)\gamma\mathcal{I}(t) \tag{6}$$

$$\dot{D}(t) = \kappa\gamma\mathcal{I}(t) \tag{7}$$

where N is the population, $\beta(t)$ is the rate of infection spread, γ is the rate of recovery or death, and κ is the probability of death conditional on infection.

[10] We may show that $\log(\Delta C_{it}) - \log(\Delta C_{i,t-7})$ approximates the average growth rate of cases from $t-7$ to t.

Confirmed cases, $C(t)$, evolve as

$$\dot{C}(t) = \tau(t)\mathcal{I}(t), \tag{8}$$

where $\tau(t)$ is the rate that infections are detected.

Our goal is to examine how the rate of infection $\beta(t)$ varies with observed policies and measures of social distancing behavior. A key challenge is that we only observed $C(t)$ and $D(t)$, but not $\mathcal{I}(t)$. The unobserved $\mathcal{I}(t)$ can be eliminated by differentiating (8) and using (5) as

$$\frac{\ddot{C}(t)}{\dot{C}(t)} = \frac{S(t)}{N}\beta(t) - \gamma + \frac{\dot{\tau}(t)}{\tau(t)}. \tag{9}$$

We consider a discrete-time analogue of equation (9) to motivate our empirical specification by relating the detection rate $\tau(t)$ to the number of tests T_{it} while specifying $\frac{S(t)}{N}\beta(t)$ as a linear function of variables $X_{i,t-14}$. This results in

$$\underbrace{\Delta \log(\Delta C_{it})}_{\frac{\ddot{C}(t)}{\dot{C}(t)}} = \underbrace{X'_{i,t-14}\theta + \epsilon_{it}}_{\frac{S(t)}{N}\beta(t)-\gamma} + \underbrace{\delta_T \Delta \log(T)_{it}}_{\frac{\dot{\tau}(t)}{\tau(t)}}$$

which is equation (M-C), where $X_{i,t-14}$ captures a vector of variables related to $\beta(t)$.

> Structural Interpretation. The component $X'_{i,t-14}\theta$ is the projection of $\beta_i(t)S_i(t)/N_i(t) - \gamma$ on $X_{i,t-14}$ (including testing variable).

Growth Rate in Deaths as Outcome. By differentiating (7) and (8) with respect to t and using (9), we obtain

$$\frac{\ddot{D}(t)}{\dot{D}(t)} = \frac{\ddot{C}(t)}{\dot{C}(t)} - \frac{\dot{\tau}(t)}{\tau(t)} = \frac{S(t)}{N}\beta(t) - \gamma. \tag{10}$$

Our measurement equation for the growth rate of deaths is based on equation (10) but account for a 21 day lag between infection and death as

$$\Delta \log(\Delta D_{it}) = X'_{i,t-21}\theta + \epsilon_{it}, \tag{M-D}$$

where

$$\Delta \log(\Delta D_{it}) := \log(\Delta D_{it}) - \log(\Delta D_{i,t-7}) \tag{11}$$

approximates the weekly growth rate in deaths from $t-7$ to t in state i. Sensitivity analysis also provides results for the case of 28 and 35 lag.

Debiased Fixed Effects Dynamic Panel Data Estimator. We apply Jackknife bias corrections; see Chen et al. (2020) and Hahn and Newey (2004) for more details. Here, we briefly describe the debiased fixed effects estimator we use.

Given our panel data with sample size (N, T), denote a set of counties by $\mathcal{N} = \{1, 2, ..., N\}$. We randomly and repeatedly partition $\mathcal{N}$ into two sets as $\mathcal{N}_1^j$ and $\mathcal{N}_2^j = \mathcal{N} \setminus \mathcal{N}_1^j$ for $j = 1, 2, ..., J$, where $\mathcal{N}_1^j$ and $\mathcal{N}_2^j$ (approximately) contain the same number of counties. For each of $j = 1, ..., J$, consider two sub-panels (where i stands for county and t stands for the day) defined by

$$\mathbf{S}_1^j = \mathbf{S}_{11}^j \cup \mathbf{S}_{22}^j \quad \text{and} \quad \mathbf{S}_2^j = \mathbf{S}_{12}^j \cup \mathbf{S}_{21}^j$$

with $\mathbf{S}_{1k}^j = \{(i,t) : i \in \mathcal{N}_k, t \leq \lceil T/2 \rceil\}$ and $\mathbf{S}_{2k}^j = \{(i,t) : i \in \mathcal{N}_k, t \geq \lfloor T/2+1 \rfloor\}$ for $k = 1, 2$, where $\lceil . \rceil$ and $\lfloor . \rfloor$ are the ceiling and floor functions. Each of these two subpanels, $\mathbf{S}_1^j$ and $\mathbf{S}_2^j$, includes observations for all cross-sectional units and time periods.

We form the estimator with bias-correction as

$$\widehat{\beta}_{\text{BC}} := 2\widehat{\beta} - \widetilde{\beta} \quad \text{with} \quad \widetilde{\beta} := \frac{1}{J}\sum_{j=1}^{J} \widetilde{\beta}_{\mathbf{S}_1^j \cup \mathbf{S}_2^j},$$

where $\widehat{\beta}$ is the standard estimator with a set of N county dummies while $\widetilde{\beta}_{\mathbf{S}_1^j \cup \mathbf{S}_2^j}$ denotes the estimator using the data set $\mathbf{S}_1^j \cup \mathbf{S}_2^j$ but treats the counties in $\mathbf{S}_1^j$ differently from those in $\mathbf{S}_2^j$ to form the estimator— namely, we include approximately $2N$ county dummies to compute $\widetilde{\beta}_{\mathbf{S}_1^j \cup \mathbf{S}_2^j}$. Thus, $(\widehat{\beta} - \widetilde{\beta})$ is the approximation to the bias of $\widehat{\beta}$, subtracting which from $\widehat{\beta}$ gives the formula given above. We set $J = 2$ in our empirical analysis. When we choose $J = 5$ for some specifications, we obtained similar results.

An alternative jacknife bias-corrected estimator is $\widehat{\beta}_{\text{CBC}} = 2\widehat{\beta} - \frac{1}{J}\sum_{j=1}^{J}(\widetilde{\beta}_{\mathbf{S}_1^j} + \widetilde{\beta}_{\mathbf{S}_2^j})/2$, where $\widetilde{\beta}_{\mathbf{S}_k^j}$ denotes the fixed effect estimator using the subpanel $\mathbf{S}_k^j$ for $k = 1, 2$. In our empirical analysis, these two cross-over jackknife bias corrected estimators give similar result; in simulation experiments, the first form performed somewhat better, so we settled out choice on it.

We report asymptotic standard errors with state-level clustering, justified by the standard asymptotic theory of bias corrected estimators. The rationale for state-level clustering is that the stochastic shocks in the model can be correlated across counties, especially within the state. A simple way to model this is to allow for the arbitrary within-state correlation and adjust the standard errors to account for this (state-level clustering).

Department of Economics and Center for Statistics and Data Science, MIT, MA 02139

Email address: vchern@mit.edu

Vancouver School of Economics, UBC, 6000 Iona Drive, Vancouver, BC.

Email address: hkasahar@mail.ubc.ca

Vancouver School of Economics, UBC, 6000 Iona Drive, Vancouver, BC.

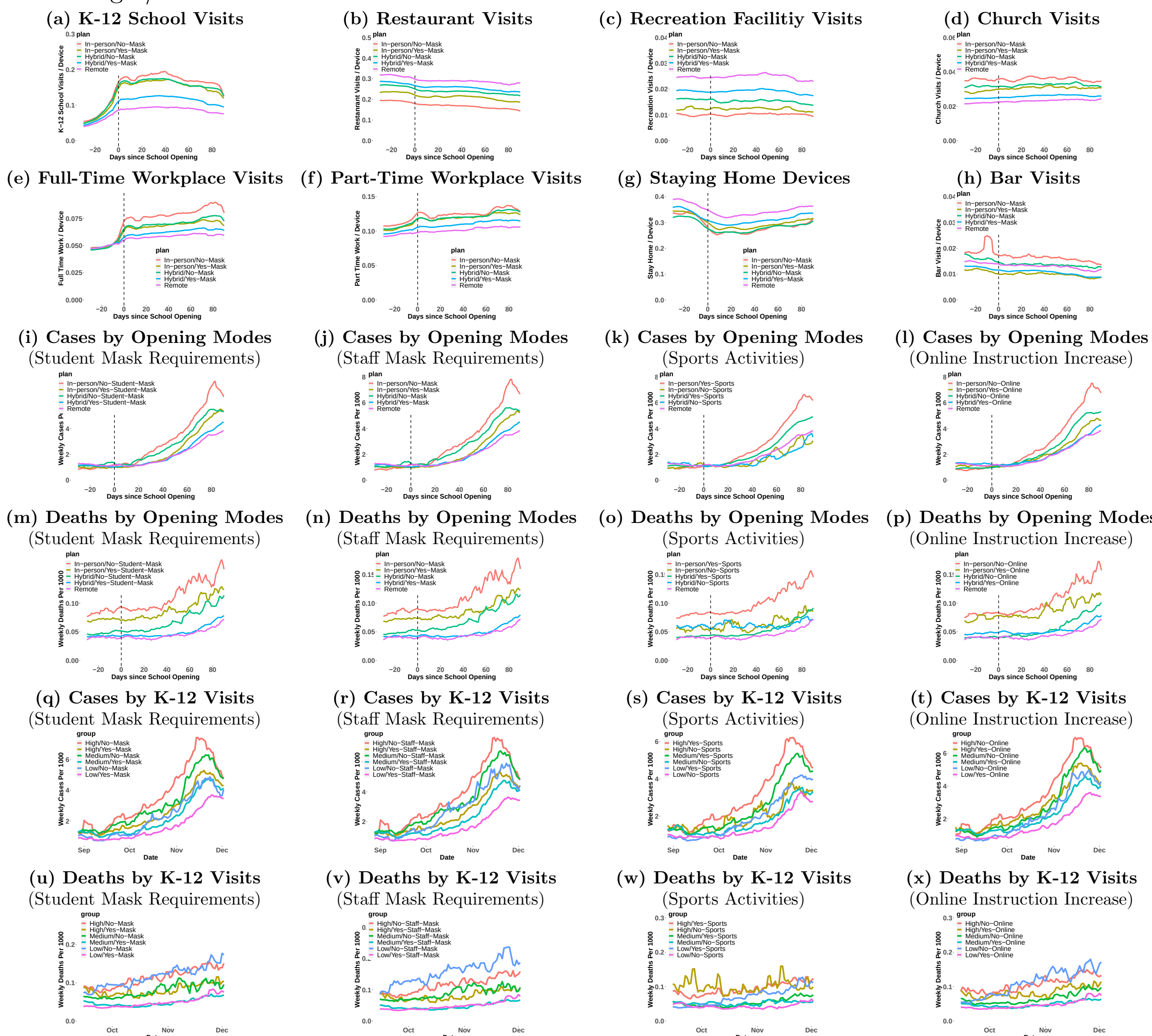
Email address: schrimpf@mail.ubc.ca

Table S1. The Association of School/College Openings and NPI Policies with Case Growth in the United States: Standard Fixed Effects Estimator without Bias Correction

	Dependent variable: ***Case Growth Rates***			
	(1)	(2)	(3)	(4)
College Visits, 14d lag	0.359***	0.412***	0.326***	0.371***
	(0.071)	(0.073)	(0.064)	(0.076)
K-12 Visits, 14d lag	0.393***	0.429***		
	(0.070)	(0.070)		
K-12 Visits × No-Mask		0.100		
		(0.070)		
K-12 In-person, 14d lag			0.062***	0.062***
			(0.017)	(0.021)
K-12 Hybrid, 14d lag			0.040***	0.033**
			(0.014)	(0.013)
K-12 Remote, 14d lag			0.030*	0.027*
			(0.016)	(0.015)
K-12 In-person × No-Mask				0.009
				(0.019)
K-12 Hybrid × No-Mask				0.032*
				(0.017)
Mandatory mask 14d lag	−0.006	−0.006	−0.015	−0.017
	(0.018)	(0.017)	(0.020)	(0.019)
Ban gatherings 14d lag	−0.066*	−0.068	−0.068**	−0.067
	(0.033)	(0.044)	(0.033)	(0.042)
Stay at home 14d lag	−0.203***	−0.198***	−0.200***	−0.200***
	(0.031)	(0.039)	(0.034)	(0.040)
log(Cases), 14d lag	−0.088***	−0.092***	−0.088***	−0.092***
	(0.009)	(0.010)	(0.010)	(0.010)
log(Cases), 21d lag	−0.042***	−0.043***	−0.043***	−0.043***
	(0.005)	(0.005)	(0.005)	(0.005)
log(Cases), 28d lag	−0.017***	−0.020***	−0.018***	−0.021***
	(0.003)	(0.003)	(0.004)	(0.004)
Test Growth Rates	0.009**	0.008*	0.009**	0.009*
	(0.004)	(0.004)	(0.004)	(0.004)
County Dummies	Yes	Yes	Yes	Yes
State× Week Dummies	Yes	Yes	Yes	Yes
Observations	690,297	545,131	612,963	528,941
R^2	0.092	0.093	0.092	0.094

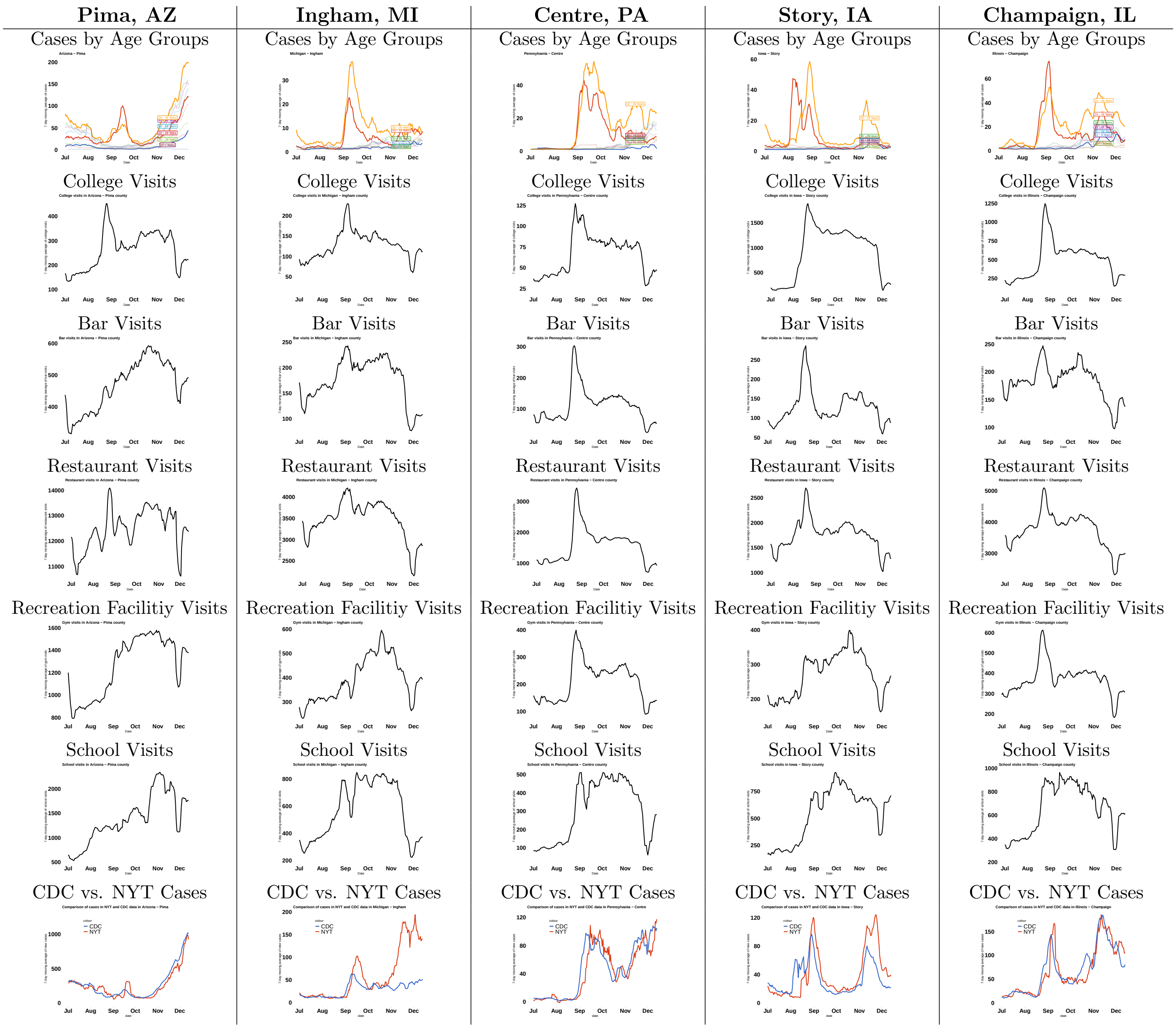
Notes: Dependent variable is the log difference in weekly positive cases across 2 weeks. Regressors are 7-day moving averages of corresponding daily variables and lagged by 2 weeks to reflect the time between infection and case reporting except that we don't take any lag for the log difference in test growth rates. All regression specifications include county fixed effects and state-week fixed effects to control for any unobserved county-level factors and time-varying state-level factors such as various state-level policies as well as 2, 3, and 4 weeks lagged log of cases. The standard fixed effects estimator without bias-correction is applied. Asymptotic clustered standard errors at the state level are reported in the bracket. *p<0.1; **p<0.05; ***p<0.01

Figure S1. Average weekly cases and deaths are associated with different modes of opening K-12 schools, visits to K-12 schools, and visits to colleges/universities



Notes: (a)-(h) plot the evolution of corresponding variables in the title before and after the day of school openings and corresponding to figures reported in Fig. 1(c)(d) in the main text. (i)-(p) corresponds to Fig.(a)(b) and plot the evolution of weekly cases or deaths per 1000 persons averaged across counties within each group of counties classified by K-12 school teaching methods and different mitigation strategies (mask requirements for students, mask requirements for staffs, allowing for sports activities, and increase in online instructions) against the days since K-12 school opening. In (i) and (m), counties that implement in-person teaching are classified into "In-person/Yes-Mask" and "In-person/No-Mask" based on whether at least one school district requires students to wear masks or not. In (k) and (o), counties that implement in-person teaching are classified into "In-person/Yes-Sports" and "In-person/No-Sports" based on whether at least one school district requires students to allow sports activities or not. In (l) and (p), counties that implement in-person teaching are classified into "In-person/No-Online" and "In-person/Yes-Online" based on whether at least one school district answer that no increase in online instruction. (q)-(x) are similar to (i)-(p) but classify counties by the volume of per-device K-12 school visits and take the calendar dates instead of the days since opening schools as x-axis, where "Low," "Middle," and "High" are county-day observations of which 14 days lagged per-device K-12 school visits less than the first quartile, between the first and the third quartiles, and larger than the third quartile, respectively. In (q) and (u), "Low/No-Mask," "Middle/No-Mask," and "High/No-Mask" are a subset of low, middle, and high visits groups of counties for which at least one school district does not require students to wear masks.

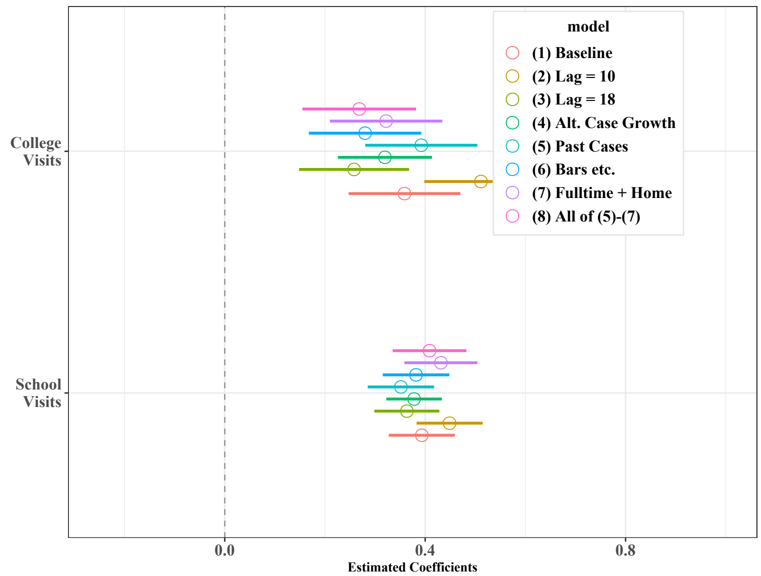
Figure S2. The number of cases by age groups and the number of visits to colleges/universities, bars, restaurants, recreation facilities, K-12 schools, and a comparison of reported cases between CDC and NYT data



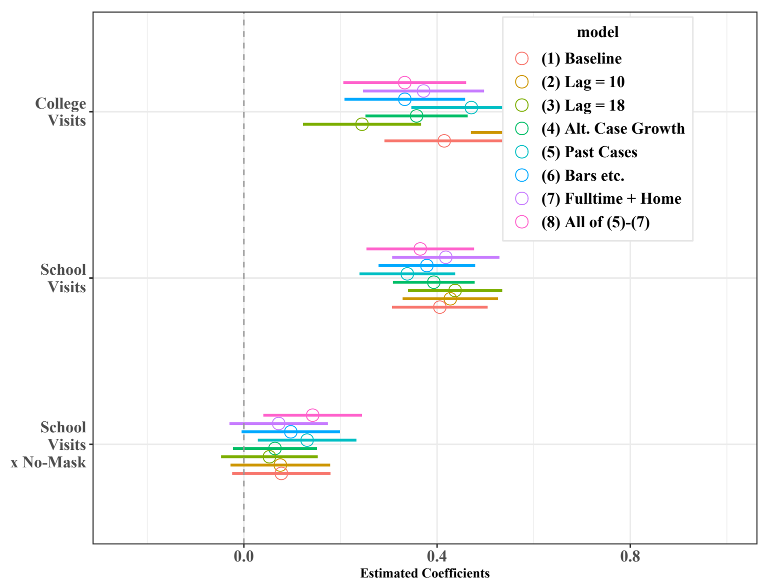
Notes: Figure corresponds to Fig. 2 in the main text but for Pima, AZ, Ingham, MI, Centre, PA, Story, IA, and Champaign, IL. Across various counties, we also report the evolution of visits to recreation facilities and K-12 school visits. The last panel at the bottom compares the sum of weekly cases across all age groups reported in CDC dataset with the weekly reported case in NYT dataset.

Figure S3. Sensitivity analysis for the estimated coefficients of K-12 visits and college visits of case growth regressions: Estimator without Bias Correction

(a) Case Growth Estimates



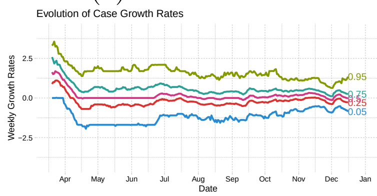
(b) Case Growth Estimates with School Visits × No Mask



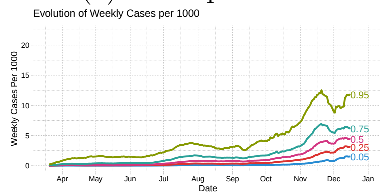
Notes: These figures corresponds to Fig. 3 of the main text but report the result of the (standard) fixed effects estimator without bias correction.

FIGURE S4. Evolution of Cases/Deaths per 1000 Persons, Case/Death Growth, Visits to K-12 Schools, Colleges, Restaurants, Bars, Gyms, Churches, K-12 School Opening Modes, and NPIs across U.S. counties

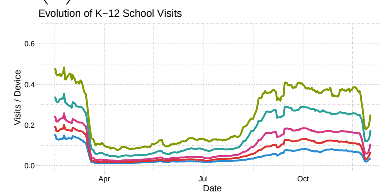
(1) Case Growth



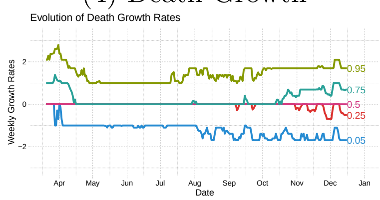
(2) Cases per 1000



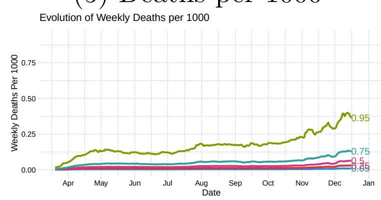
(3) Visits to K-12 Schools



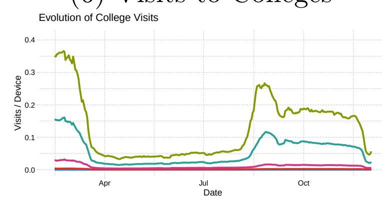
(4) Death Growth



(5) Deaths per 1000

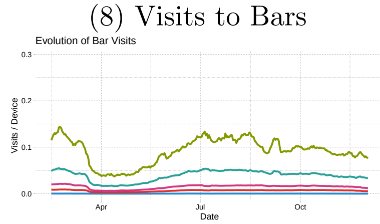


(6) Visits to Colleges

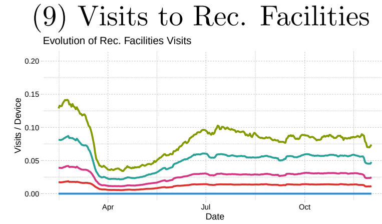


(7) Visits to Restaurants

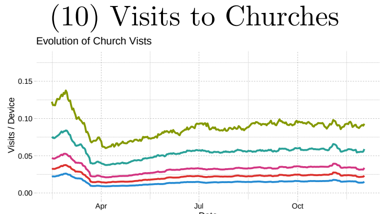
(8) Visits to Bars



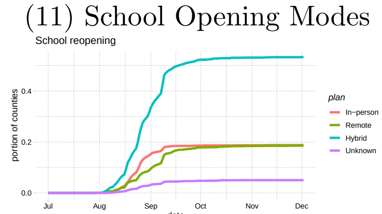
(9) Visits to Rec. Facilities



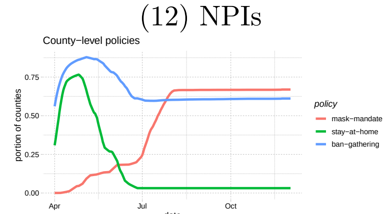
(10) Visits to Churches



(11) School Opening Modes



(12) NPIs



Notes: (1)-(10) report the evolution of various percentiles of corresponding variables in the title over time. (10) reports the proportion of counties that open K-12 schools with different teaching methods including “Unknown” over time while (11) reports the proportion of counties that implement three NPIs over time.

TABLE S2. The Association of School/College Openings with Mobility in the United States: All Estimates

(a) Full-time Workplace Visits and Staying Home Devices

	Dependent variable			
	Full Time (1)	Full Time (2)	Stay Home (3)	Stay Home (4)
College Visits	−0.080***	−0.098***	−0.207***	−0.207***
	(0.004)	(0.006)	(0.024)	(0.026)
K-12 School Visits	0.078***		−0.061**	
	(0.006)		(0.026)	
Open K-12 In-person		0.999***		−2.271***
		(0.125)		(0.382)
Open K-12 Hybrid		0.509***		0.094
		(0.051)		(0.186)
Open K-12 Remote		0.211***		0.159
		(0.048)		(0.307)
Mandatory mask	−0.152***	−0.306***	0.204	0.222
	(0.042)	(0.053)	(0.260)	(0.250)
Ban gatherings	0.067	0.097*	0.870	0.754
	(0.047)	(0.051)	(0.561)	(0.521)
Stay at home	−0.039	−0.028	2.881***	2.895***
	(0.031)	(0.033)	(0.330)	(0.340)
log(Cases), 14d lag	0.004	0.007	0.273***	0.273***
	(0.004)	(0.005)	(0.028)	(0.028)
log(Cases), 21d lag	0.002	−0.001	0.283***	0.281***
	(0.002)	(0.003)	(0.019)	(0.017)
log(Cases), 28d lag	0.006***	0.005*	0.221***	0.215***
	(0.002)	(0.002)	(0.023)	(0.024)
County Dummies	Yes	Yes	Yes	Yes
State× Week Dummies	Yes	Yes	Yes	Yes
Observations	670,909	595,886	670,909	595,886
R^2	0.870	0.853	0.889	0.888

(b) Visits to Restaurants and Bars

	Dependent variable			
	Restaurants (1)	Restaurants (2)	Bars (3)	Bars (4)
College Visits	0.064	0.034	0.016***	0.012**
	(0.053)	(0.051)	(0.006)	(0.005)
K-12 School Visits	0.006		0.008	
	(0.046)		(0.006)	
Open K-12 In-person		−1.367***		−0.177***
		(0.404)		(0.041)
Open K-12 Hybrid		−1.162***		−0.097***
		(0.272)		(0.038)
Open K-12 Remote		−0.512*		0.031
		(0.295)		(0.056)
Mandatory mask	0.542	0.037	0.191***	0.113
	(0.371)	(0.403)	(0.067)	(0.069)
Ban gatherings	0.067	0.135	−0.066	−0.070
	(0.920)	(0.897)	(0.117)	(0.118)
Stay at home	−2.232***	−2.170***	−0.228***	−0.204***
	(0.203)	(0.241)	(0.025)	(0.025)
log(Cases), 14d lag	−0.096**	−0.072	−0.010*	−0.004
	(0.047)	(0.050)	(0.006)	(0.007)
log(Cases), 21d lag	−0.084***	−0.087***	−0.011**	−0.009*
	(0.032)	(0.032)	(0.005)	(0.005)
log(Cases), 28d lag	−0.150***	−0.161***	−0.014**	−0.015***
	(0.043)	(0.042)	(0.005)	(0.005)
County Dummies	Yes	Yes	Yes	Yes
State× Week Dummies	Yes	Yes	Yes	Yes
Observations	670,909	595,886	670,909	595,886
R^2	0.881	0.883	0.807	0.807

Notes: These tables report the omitted estimates of Table 2 in the main text. All regression specifications include county fixed effects and state-week fixed effects. The debiased estimator is used. Clustered standard errors at the state level are reported in the bracket. *p<0.1; **p<0.05; ***p<0.01

Table S3. The Association of School/College Openings, NPI Policies, Full-time/Part-time Work, and Staying Home Devices with Case Growth in the United States: Debiased Fixed Effects Estimator

	Dependent variable: ***Case Growth Rates***			
	(1)	(2)	(3)	(4)
College Visits, 14d lag	0.060	0.012	0.114^{*}	0.010
	(0.071)	(0.072)	(0.065)	(0.075)
K-12 Visits, 14d lag	0.393^{***}	0.283^{***}		
	(0.075)	(0.087)		
K-12 Visits × No-Mask		0.287^{***}		
		(0.071)		
K-12 In-person, 14d lag			0.015	−0.007
			(0.016)	(0.020)
K-12 Hybrid, 14d lag			-0.028^{**}	-0.055^{***}
			(0.013)	(0.013)
K-12 Remote, 14d lag			-0.094^{***}	-0.115^{***}
			(0.015)	(0.014)
K-12 In-person × No-Mask				0.034^{*}
				(0.020)
K-12 Hybrid × No-Mask				0.043^{***}
				(0.017)
Full-time Work Device, 14d lag	−0.117	0.186	0.956^{**}	0.967^{**}
	(0.417)	(0.490)	(0.384)	(0.436)
Part-time Work Device, 14d lag	0.262	0.466	0.820^{***}	0.915^{***}
	(0.259)	(0.305)	(0.276)	(0.309)
Staying Home Device, 14d lag	-0.290^{***}	-0.283^{***}	-0.352^{***}	-0.332^{***}
	(0.057)	(0.069)	(0.061)	(0.067)
Mandatory mask 14d lag	-0.114^{***}	-0.124^{***}	-0.128^{***}	-0.128^{***}
	(0.018)	(0.017)	(0.019)	(0.019)
Ban gatherings 14d lag	-0.120^{***}	-0.127^{***}	-0.125^{***}	-0.126^{***}
	(0.034)	(0.044)	(0.034)	(0.043)
Stay at home 14d lag	-0.246^{***}	-0.241^{***}	-0.232^{***}	-0.239^{***}
	(0.033)	(0.040)	(0.034)	(0.040)
log(Cases), 14d lag	-0.100^{***}	-0.101^{***}	-0.096^{***}	-0.098^{***}
	(0.009)	(0.010)	(0.010)	(0.010)
log(Cases), 21d lag	-0.060^{***}	-0.059^{***}	-0.059^{***}	-0.058^{***}
	(0.004)	(0.005)	(0.005)	(0.005)
log(Cases), 28d lag	-0.030^{***}	-0.033^{***}	-0.030^{***}	-0.033^{***}
	(0.003)	(0.003)	(0.004)	(0.003)
Test Growth Rates	0.009^{**}	0.008^{*}	0.009^{**}	0.009^{**}
	(0.004)	(0.004)	(0.004)	(0.004)
County Dummies	Yes	Yes	Yes	Yes
State× Week Dummies	Yes	Yes	Yes	Yes
Observations	690,297	545,131	612,963	528,941
R^2	0.092	0.093	0.092	0.094

Notes: Dependent variable is the log difference in weekly positive cases across 2 weeks. All regression specifications include county fixed effects and state-week fixed effects to control for any unobserved county-level factors and time-varying state-level factors such as various state-level policies. The debiased fixed effects estimator is applied. Asymptotic clustered standard errors at the state level are reported in the bracket. *p<0.1; **p<0.05; ***p<0.01

Table S4. The Association of School/College Openings and NPI Policies with Death Growth in the United States: Debiased Fixed Effects Estimator

	Dependent variable: ***Death Growth Rates***			
	(1)	(2)	(3)	(4)
College Visits, 21d lag	0.142***	0.181***	0.189***	0.170***
	(0.047)	(0.057)	(0.058)	(0.055)
K-12 Visits, 21d lag	0.160***	0.060		
	(0.048)	(0.066)		
K-12 Visits × No-Mask		0.174**		
		(0.073)		
K-12 In-person, 21d lag			−0.002	−0.012
			(0.019)	(0.019)
K-12 Hybrid, 21d lag			0.013	0.014
			(0.014)	(0.014)
K-12 Remote, 21d lag			0.018	0.015
			(0.015)	(0.017)
K-12 In-person × No-Mask				0.050***
				(0.016)
K-12 Hybrid × No-Mask				0.017
				(0.015)
Mandatory mask, 21d lag	−0.019**	−0.018**	−0.028***	−0.023**
	(0.009)	(0.009)	(0.009)	(0.009)
Ban gatherings, 21d lag	−0.044	−0.056**	−0.053**	−0.055**
	(0.027)	(0.025)	(0.027)	(0.025)
Stay at home, 21d lag	−0.087***	−0.076**	−0.078***	−0.067**
	(0.032)	(0.030)	(0.030)	(0.029)
log(Deaths), 21d lag	−0.053***	−0.049***	−0.052***	−0.047***
	(0.004)	(0.005)	(0.004)	(0.006)
log(Deaths), 28d lag	−0.036***	−0.041***	−0.037***	−0.042***
	(0.004)	(0.005)	(0.005)	(0.005)
log(Deaths), 35d lag	−0.031***	−0.032***	−0.032***	−0.033***
	(0.004)	(0.005)	(0.004)	(0.005)
County Dummies	Yes	Yes	Yes	Yes
State× Week Dummies	Yes	Yes	Yes	Yes
Observations	628,061	490,568	557,219	476,794
R^2	0.049	0.050	0.050	0.051

Notes: Dependent variable is the log difference in weekly reported deaths across 2 weeks. Regressors are 7-day moving averages of corresponding daily variables and lagged by 3 weeks to reflect the time between infection and case reporting. All regression specifications include county fixed effects and state-week fixed effects to control for any unobserved county-level factors and time-varying state-level factors such as various state-level policies. The debiased fixed effects estimator is applied. Asymptotic clustered standard errors at the state level are reported in the bracket. Estimates are based on the sample of counties after dropping the smallest 10 percent in population sizes because the number of reported deaths is zero for many observations in small counties. *p<0.1; **p<0.05; ***p<0.01

Table S5. Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Case Growth Rate	698,278	0.099	0.901	−8.107	−0.288	0.495	8.002
Death Growth Rate	698,278	0.023	0.790	−6.170	0.000	0.000	6.170
log(Cases)	703,702	2.829	2.140	−1.000	1.386	4.331	10.488
log(Deaths)	703,702	−0.269	1.147	−1.000	−1.000	0.000	6.479
College Visits	728,228	0.010	0.031	0.000	0.000	0.008	1.827
K-12 School Visits	728,228	0.074	0.072	0.000	0.024	0.103	1.167
K-12 opening, in-person	646,816	0.079	0.207	0.000	0.000	0.000	1.000
K-12 opening, Hybrid	646,816	0.224	0.357	0.000	0.000	0.424	1.000
K-12 opening, Remote	646,816	0.078	0.227	0.000	0.000	0.000	1.000
No-Mask for Staffs	577,680	0.293	0.455	0.000	0.000	1.000	1.000
Mandatory Mask	728,944	0.461	0.495	0	0	1	1
Ban Gathering	728,944	0.658	0.472	0	0	1	1
Stay at Home	728,944	0.143	0.345	0	0	0	1
Full Time Workplace Visits	728,206	0.054	0.018	0.010	0.042	0.061	0.484
Part Time Workplace Visits	728,206	0.101	0.025	0.023	0.084	0.113	0.567
Staying Home Devices	728,206	0.342	0.116	0.021	0.267	0.393	3.657
Recreational Place Visits	728,228	0.017	0.022	0.000	0.000	0.026	0.786
Church Visits	728,228	0.025	0.018	0.000	0.014	0.032	0.583
Drinking Place Visits	728,228	0.012	0.024	0.000	0.0001	0.015	1.461
Restaurant Visits	728,228	0.250	0.175	0.000	0.150	0.315	4.261
Test Growth Rates	698,278	0.067	1.099	−13.616	−0.051	0.178	13.111
Population in 2018 (millions)	706,966	0.104	0.331	0.0002	0.012	0.071	10.106

Notes: Based on observations from April 15, 2020 to December 2, 2020 for the maximum of 3142 counties.

Table S6. Correlation across variables

	College Visits	K-12 School Visits	Open K-12 In-person	Open K-12 Hybrid	Open K-12 Remote	No-Mask for Staffs	Mandatory mask	Ban gatherings	Stay at home	Full-time Workplace Visits	Part-time Workplace Visits	Staying Home Devices	Bar Visits	Restaurant Visits	Rec. Facilities Visits	Church Vists
College Visits	1.00															
K-12 School Visits	0.09	1.00														
Open K-12 In-person	0.05	0.43	1.00													
Open K-12 Hybrid	0.11	0.44	0.04	1.00												
Open K-12 Remote	0.05	0.09	-0.06	-0.06	1.00											
No-Mask for Staffs	0.01	0.16	0.15	-0.02	-0.10	1.00										
Mandatory mask	0.09	0.10	0.03	0.24	0.23	-0.31	1.00									
Ban gatherings	-0.03	-0.14	-0.09	-0.06	0.00	-0.03	-0.09	1.00								
Stay at home	-0.06	-0.24	-0.14	-0.21	-0.13	-0.08	-0.19	0.20	1.00							
Full-time Workplace Visits	0.04	0.56	0.37	0.36	0.10	0.12	0.05	-0.17	-0.21	1.00						
Part-time Workplace Visits	0.06	0.60	0.32	0.34	0.04	0.20	-0.01	-0.12	-0.31	0.71	1.00					
Staying Home Devices	-0.04	-0.27	-0.18	-0.23	-0.02	-0.10	0.01	-0.00	0.27	0.06	-0.19	1.00				
Bar Visits	0.05	0.08	0.02	-0.02	0.01	0.08	0.01	-0.06	-0.08	0.12	0.11	0.15	1.00			
Restaurant Visits	0.17	0.02	-0.10	0.00	0.06	-0.10	0.14	0.10	-0.08	-0.07	0.07	0.04	0.34	1.00		
Rec. Facilities Visits	0.15	-0.00	-0.07	0.03	0.11	-0.08	0.18	0.03	-0.08	-0.05	-0.03	0.09	0.26	0.52	1.00	
Church Vists	0.06	0.32	0.13	0.08	-0.03	0.17	-0.06	-0.07	-0.16	0.15	0.37	-0.18	0.11	0.18	0.03	1.00

Notes: Based on observations from April 15, 2020 to December 2, 2020 for the maximum of 3142 counties.